FACULTEIT ECONOMIE EN
BEDRIJFSWETENSCHAPPEN

KATHOLIEKE
UNIVERSITEIT
LEUVEN

TIMING IS MONEY

In Search of the Role of Timing in Marketing Decisions and Effectiveness

Proefschrift voorgedragen
tot het behalen van de graad
van Doctor in de Toegepaste
Economische Wetenschappen

door

Maarten GIJSENBERG

Nummer 316 2009

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Plus est en vous

Ah those days, those days where did they go?
They shuffled through our doorways
Are they here?
Ah those days, those days they follow us home
And peer through our windows
And they're here?

For all our hoping,
They're here

Our yesterdays tomorrows
They're here

For all our hoping, all our wondering
They're here

(Stuart Staples)

ACKNOWLEDGEMENTS

Dit is het dan. Dit boekje. Mijn doctoraatsthesis. Het resultaat van een tocht van bijna vijf jaar. Geeft het alles weer wat die vijf jaar betekend hebben? Alles wat ik geleerd heb? Alles wat ik gezien, beleefd heb? De indrukken die me zullen bijblijven? Zeker niet. Het is slechts een ansichtkaart van mijn tocht. Het laat zeker niet het volledige traject zien. Het geeft enkele vlugge indrukken, een impressie van wat er op mijn weg lag, plaatsen waar ik ben geweest.

Onvoorbereid op reis vertrekken. Het is iets wat niet in mijn aard ligt. En toch, toch ben ik eigenlijk zo aan deze tocht begonnen. Wat te verwachten? Geen idee… In de loop van de tijd zijn er echter tal van mensen geweest die mij in de juiste richting gidsten, die me afleiding boden en op wie ik heb kunnen steunen.

Eerst en vooral waren er natuurlijk mijn beide promotoren, Marnik Dekimpe en Jan-Benedict Steenkamp. Als ik eerlijk ben, moet ik toegeven dat, toen ik een vijftal jaar geleden bij hen op gesprek ging, ik eigenlijk niet wist wie ze waren. Er was een vacature op een interessant project dat handelde over reclame, en de professor hier in Leuven die de leiding had bleek volgens een aantal vrienden een sympathieke man te zijn. Pas achteraf ontdekte ik hun vitae. En moest ik slikken. Had ik die vooraf beter bestudeerd en ingeschat, zou ik waarschijnlijk de stap zelfs niet hebben durven te zetten. Anderzijds, het voorrecht om met dergelijke gidsen op pad te gaan, kon ik niet aan mij voorbij laten gaan.

Marnik, we hebben samen een lange weg afgelegd. In het begin was deze al eens wat ruw, met allerhande putten en gaten, bochten en hellingen, maar geleidelijk zijn we op rustigere wegen beland. Ik apprecieer enorm de manier waarop je mij stap voor stap in een goede richting hebt weten te sturen, evenals de manier waarop we zijn gaan samenwerken. Tijdens mijn tocht ben ik al eens op de nodige obstakels gestoten, maar jij hebt er mij leren mee omgaan, en er het positieve uit te halen. Kritisch blijven voor je eigen ideeën en werk is zeker iets wat ik onthoud van onze

samenwerking. Ik hoop dan ook dat we komende jaren elkaar nog vaak mogen tegenkomen op onze wegen.

Jan-Benedict, de gepassioneerde manier waarop jij aan onderzoek doet, kan niet anders dan anderen aansteken. Tomeloze energie, een overvloed aan ideeën, rake analyses. Jouw inzichten hielpen ons zeker de juiste strategische keuzes te maken, en zorgden ervoor dat we niet verdwaalden op onze weg. Ik vind het een eer met jou te mogen samenwerken, en dank je voor je co-promotorschap.

Naast mijn promotoren wil ik zeker ook Harald van Heerde, Vincent Nijs, Luk Warlop en Valarie Zeithaml, de andere leden van mijn commissie, bedanken. Harald, jij wees me de weg over de steile hellingen van de Bayesiaanse wereld, en zorgde ervoor dat het een echte avonturentocht werd die me zelfs naar het andere eind van de planeet voerde. Op een rustige manier motiveerde je mij om telkens weer dat stapje verder te gaan. Je bent er zelfs in geslaagd om mij statistiek en programmeren leuk te laten vinden, iets wat ik nooit had kunnen denken. Ik kijk er dan ook enorm naar uit om verder te trekken in jouw gezelschap. Vincent, hartelijk dank voor jouw steun bij het zetten van mijn eerste stappen in het onderzoek, zeker ook voor wat betreft het leren werken met gigantische datasets. Jouw coaching heeft een niet te onderschatten rol gespeeld om me door een aantal moeilijke fases heen te helpen. Luk, als relatieve buitenstaander zorgde jouw frisse kijk ervoor dat ik meermaals schijnbare evidenties toch weer in vraag diende te stellen, wat zeker bijdroeg tot de waarde van mijn doctoraat. Valarie, you joined the committee in the last part of the PhD. I am honoured by the interest a distinguished scholar like you is showing in my work, and I am very pleased to have you in my committee. Your questions and remarks are highly appreciated and can only add value to this work.

Onderweg kreeg ik ook het gezelschap van andere reizigers. Sommigen heb ik maar kort gekend, anderen bleven langer, met een aantal heb ik samen een behoorlijk stuk weg afgelegd. Daarom wil ik dan ook mijn voormalige en huidige collega's, in Leuven, Mons en elders, binnen en buiten Marketing, danken voor de manier waarop ze deze jaren gekleurd hebben. Elk van jullie weet wel wat hij of zij voor mij

betekend heeft. Toch wil ik enkele mensen speciaal vermelden. Eerst en vooral Sarah, Miriam en Liesbeth, en dit onder andere voor de talloze koffiepauzes die we samen hielden. Soms kort, soms lang, soms ronduit hilarisch, soms eerder filosofisch, maar steeds weer een bron van energie. Daarnaast zeker ook Isabel en Patricia. Op drie verschillende plaatsen begonnen we tegelijk aan dit avontuur. Alle drie schreven we een totaal ander verhaal, volgden we heel andere wegen. En toch begrepen we als lotgenoten nog het best elkaars verhalen. Kobe, de intense discussies die we hadden tijdens onze tijd samen op kantoor zullen me altijd bijblijven. Jiska, zo anders dan ik, en toch ook weer niet, vond ik in jou een geweldig (bureau)maatje.

Op mijn tocht botste ik opvallend vaak op oude bekenden. Vrienden die zorgden voor de nodige afleiding, en die er mij op tijd en stond aan herinnerden dat er buiten dit doctoraat nog zoveel leuks en interessants was en is. Zij kenden me al van voor ik dit plan opvatte, en lieten het me voelen wanneer ik mij weer eens te ver liet meevoeren. Tienne, ons voorzittersjaar bij de Kring voor Internationale Betrekkingen, in een onmogelijke combinatie met het eerste jaar van mijn doctoraat, was een onvergetelijke tijd. Maaike en Anna, bedankt voor alle uren dat jullie naar mijn verhalen wilden luisteren, maar evenzeer voor alle leuke momenten, zeker ook samen met Karolien en Isabel. Inge, Isabelle, ook al liepen en lopen onze wegen niet altijd samen, bedankt dat jullie er waren.

Zonder mijn ouders, echter, zou ik vermoedelijk zelfs nooit op weg gegaan zijn. Zij leerden me om doordachte keuzes te maken, en dan volledig voor deze keuzes te gaan. Wat je doet, doe dat goed. Zij leerden me door te zetten, ook al zitten de omstandigheden soms heel erg tegen. Ook al waren de wegen die ik de voorbije jaren volgde hen niet altijd even duidelijk, ook al deed ik hen niet altijd recht, toch zijn ze mij blijven steunen. Mams, paps, bedankt. Bedankt ook Joris en Hilde, voor alles. En een glimlach van Pippa en Abel deed meteen zelfs de grootste tegenslag vergeten.

Helemaal in het begin van mijn tocht kwam ik echter nog iemand tegen die in de loop van de jaren meermaals mijn pad zou kruisen, telkens weer op andere plaatsen, telkens weer onder andere omstandigheden, tot de muziek ons exact een jaar geleden echt samenbracht. Sara, als er een constante is tussen ons, dan is het wel reizen. In jou heb ik alvast een fantastische reisgenote gevonden, en ik hoop dan ook dat we nog lang samen verder mogen trekken. De voorbije maanden waren niet altijd even gemakkelijk, samen op de laatste steile helling. Jouw begrip, rust en steun hebben er voor gezorgd dat ook die laatste klip genomen werd. Bedankt.

Deze tocht zit erop. Maar dit is geen einde.

Dit is een begin.

Leuven, 6 juli 2009

Við Vorum Sammála Um Það

Sammála Um Flesta Hluti

Við Munum Gera Betur Næst

Þetta Er Ágætis Byrjun*

(Sigur Rós)

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I

INTRODUCTION

I.1. THE ROLE OF TIMING IN MARKETING DECISIONS AND EFFECTIVENESS

One of the most fundamental changes the marketing profession has experienced over the past decade, is the gradual shift in the way firms look upon marketing expenditures. Once treated as mere costs, they are now considered more and more to be investments that should deliver shareholder value (e.g. Srivastava et al., 1998). Firms want to realize the highest possible returns on their investments, and marketing investments are no exception to this. It should hence not come as a surprise that a recent survey among senior marketing managers showed that exactly improvement of the performance and the accountability of the marketing organization are two of the main focuses of senior level marketing practitioners (CMO Council, 2009). In addition, for the second time in a row, return on investment and accountability of marketing expenditures have been included in the Marketing Science Institute Research Priorities (Marketing Science Institute, 2008): *"…companies are more interested than ever in understanding and measuring the returns being obtained from marketing investments. This includes the returns to advertising, both long and short term…"* Measuring, understanding and improving the effectiveness of marketing investments has thus become of central interest to marketing practitioners as they experience more and more pressure to justify these investments. One of the crucial determinants of the success of marketing investments, i.e. the timing of the investments (see e.g. Bagozzi and Silk, 1983; Kent and Allen, 1994), will therefore be the focus of this dissertation. Knowing and understanding its role in marketing decisions and in the effectiveness of marketing mix instruments are elementary prerequisites in developing effective strategies to maximize their performance and returns.

When the success of marketing investments in general depends on the timing of these investments, this certainly applies for advertising investments. Timing and magnitude of such investments, together, have been shown to be central drivers of advertising effectiveness (e.g. Danaher et al., 2008). Advertising response has been shown to follow an s-shaped function (e.g. Vakratsas et al., 2007). This implies that a certain threshold level of advertising has to be passed before it will get noticed and resort any effects. On the other hand, advertising is also characterized by diminishing returns to scale (e.g. Tellis, 2007). Determining the appropriate level of advertising above the threshold level but before the leveling off of returns becomes too strong is crucial. In addition, carry-over effects enable firms to apply dynamic advertising strategies, as effects of current advertising investments will persist for some time in the future (e.g. Leone, 1995). Firms thus do not have to advertise every single week, but can capitalize on their investments during previous periods.

Firms, on the other hand, are not acting in a void. Their products are competing with other offerings for the attention of, and ultimately the purchase by, consumers. Competitive interference by means of competitive clutter can seriously hamper the firms' efforts in doing so (e.g. Assael, 1998). This competitive clutter is essentially a combination of (i) the number of competitors that is advertising, and (ii) the total amount of advertising by these firms (Danaher et al., 2008). It was shown that especially the number of competing messages will play a crucial role in the reduction of the own advertising effectiveness (Danaher et al., 2008). Being able to understand when to expect competitors' advertising, in combination with the total expected magnitude of their advertising therefore becomes crucial. It enables firms to avoid competitive interference, thereby increasing the effectiveness of the own investments. An investigation of the drivers behind the timing and magnitude of observed advertising spending patterns will therefore be the subject of the first study in this dissertation.

However, the returns that will be obtained on marketing investments will not only depend on the timing and magnitude of individual campaigns, but are also time-dependent in an other dimension. Results can to a large extent be affected by the general macro-economic situation. The recent economic crisis abruptly reminded firms of this. In December 2008, US retail sales declined with 9.8% compared to the 2007 holiday season. It was the sixth consecutive month of decline, the longest recorded negative sequence ever (The Financial Times, 2009). Tiffany&Co, the renowned luxury jewelry specialist, reported a decrease of its sales by 21% compared to the holiday season of 2007, and car sales even dropped with an astonishing 36%. During economic downturns, consumers' attitudes and expectations are altered. This, in turn, will have serious implications on their actual purchasing behavior, and the decision making process behind it (Katona, 1975). The uncertainty incorporated in such crises, especially concerning consumers' future revenues, makes the latter loose trust. As a reaction, thereby encouraged by possibly reduced disposable incomes, they reduce or postpone their expenditures, and focus more on functional relative to hedonic features. Thus, their susceptibility to certain marketing mix instruments may change.

The fact that consumers may react differently to marketing actions across the business cycle is a crucial observation, especially as it has been shown that marketing investments are often pro-cyclical (e.g. De Chernatoy et al., 1992; Deleersnyder et al., 2009). During economic downturns, e.g. advertising will be reduced, and fewer new products will be launched. As some marketing mix instruments may be relatively less effective during contractions versus expansions in generating returns, knowing which instrument evolves in which direction becomes of central interest to firms. Marketing budgets, under ever increasing pressure to prove their effectiveness, become even more scrutinized during recessions. Insights in the effectiveness evolutions thus help firms choosing the right strategies during economic downturns. In our second essay, we therefore target two important marketing mix instruments, i.e. advertising and price, and study their effectiveness evolution across the business cycle.

I.2. UNDERSTANDING THE TIMING AND MAGNITUDE OF ADVERTISING SPENDING PATTERNS

Over the past decades, an impressive body of research has focused on advertising effectiveness (see e.g. Tellis and Ambler, 2007 for a recent overview). Observed advertising spending patterns, however, have received much less attention in the literature. Still, considerable variation exists in advertising spending (i) within the same brand over time, (ii) across brands in the same categories, and (iii) across categories. Understanding why brands start/stop advertising, in addition, remains very relevant to both advertising media and advertisers. The former will benefit from a profound understanding of the purchase behavior of their customers, i.e. the spending patterns of advertising brands. Advertisers, in turn, are interested in accurate predictions on the expected timing and magnitude of their competitors' spending. This should enable them to gauge the extent of competitive interference they may expect, thus increasing the effectiveness of their investments (cfr. Danaher et al., 2008).

Although observed advertising spending patterns have received little attention in the *empirical* literature, a substantial stream of *normative* literature has been devoted to the timing of advertising actions. These studies provide evidence on optimal advertising schedules in order to maximize the effectiveness of the invested budgets. Starting from even advertising schedules (e.g. Zielske, 1959; Sasieni, 1971; 1989) and as a result of the inclusion of more and more real-world effects (e.g. Mahajan and Muller, 1986; Mesak, 1992; Park and Hahn, 1991; Naik et al., 1998), it is now widely accepted that in most instances, so-called pulsing advertising schedules are optimal. Such pulsing schedules, differing from even ones, alternate between (i) high and (ii) low or zero levels of advertising. These studies, although insightful on the optimality of pulsed over even spending, remain vague on some crucial implementation issues, including (i) how often to advertise, (ii) how many weeks an advertising pulse or campaign should last, and (iii) how much should be spent.

Finally, (iv) they do not provide insights on the observed behavioral differences across brands and categories.

In our first study, we build upon the insights and guidelines of the normative literature to explain observed advertising spending patterns. We provide evidence of the acceptance and implementation of the findings of this literature in the market. Advertising expenditures, as observed in real world data, indeed show patterns which can best be described as pulses or campaigns, with pulses in the last case lasting for several weeks (Doganoglu and Klapper, 2006). In our dataset, for instance, only 6 of the 748 included brands advertise permanently, and while doing so, they as well alternate between high and lower levels of advertising.

The observed advertising campaigns are characterized by two main phenomena. On the one hand, do they show a state dependence, in the sense that advertising will be continued for several weeks once it has started. The likelihood of a brand advertising in a certain week will hence be larger if that brand was also advertising during the previous week. This state dependence will be captured by the Adstock concept (e.g. Broadbent, 1984), as it accounts for advertising goodwill created by previous advertising. During a campaign, advertising goodwill will be built. This goodwill will decay when the brand no longer advertises. Brands thus continue advertising at relatively higher levels of advertising goodwill, while not advertising at relatively lower levels. On the other hand, advertising campaigns also express the dynamics of advertising pulsing behavior, in which brands start and stop advertising, without continuing all the time. Brands can be expected to start advertising as soon as the goodwill level they have created by previous advertising has fallen below a certain minimum level. By means of their campaign, they will rebuild their advertising goodwill stock. At a certain moment in time, the resulting stock will have attained a desired maximum level, and the brand decides to end the campaign. As such, observed advertising spending shows strong resemblance with so-called (s,S) inventory management systems that keep stocks between a minimum level s and a maximum level S. Although well-known and often applied in logistics (e.g. Silver et al., 1998), such systems have been cited only very few times in advertising research (Zufryden, 1973; Doganoglu and Klapper, 2006). Given the strong similarities between such systems and our active Adstock management system, we embed the latter in an (s,S) inventory management system by means of the novel Ad-sensor concept.

However, given the aforementioned limitations in the normative literature on some crucial implementation issues of advertising pulsing strategies, we as well investigate to what extent observed patterns depend on a set of widely cited factors influencing advertising budgeting decisions. These factors can be grouped into three main sets which are commonly considered by brands when drawing up their marketing decisions: (i) Company factors, (ii) Competitive factors, and (iii) Category or marketplace factors (Montgomery et al., 2005). Thus we are able to provide a broad view on what is driving advertising spending patterns as we can observe in the market.

I.3. ADVERTISING AND PRICE EFFECTIVENESS OVER THE BUSINESS CYCLE

A second and completely different way of looking at the role of timing in marketing, is the investigation of how, at a macro-level, the intensity and effectiveness of marketing investments evolve over the business cycle. The returns firms can achieve by investing in marketing actions will not only depend on an effective scheduling of individual campaigns. Budgets available, the effectiveness of the different marketing mix instruments, and hence the optimal allocation of budgets over those instruments in order to achieve maximal returns, may be time-dependent, as they are all likely to be affected by the overall economic situation.

This is an important insight, as firms are under an ever increasing pressure to justify their marketing expenditures. This pressure will be even higher during economic contractions, when every dollar matters more. The recent economic crisis forced many managers to actively reconsider their marketing decisions (McKinsey, 2009). Marketing budgets are cut, and especially advertising budgets become scrutinized. By January 2009, 71% of all marketing managers had already reduced their advertising budgets, and 77% was planning to economize further on media expenditures (Advertising Age, 2009). Managers are more than ever focusing on returns and accountability (CMO Council, 2009), areas in which marketing investments suffer from a history of relatively low credibility

This tendency to reduce marketing budgets during economic downturns has been well documented in a growing stream of articles on the intensity of marketing investments over the business cycles. During economic sour times, firms will economize on innovation and new product introductions (e.g. Devinney, 1990; Axarloglou, 2003). At an aggregate level, Deleersnyder et al. (2009) provided evidence of the pro-cyclical behavior of advertising budgets, with reductions during economic contractions and increases during economic upbeat times. Similar patterns were found at the firm level by Frankenberger and Graham (2003) and at the brand level by Lamey et al. (2007). These reductions in advertising budgets are not only a consequence of overall across-the-board cost-cutting (Srinivasan and Lilien, 2009), but are as well the result of a shift in budgets to those instruments which are more likely to create positive short run effects. Price promotions and couponing therefore become relatively more popular during contractions (e.g. de Chernatony et al., 1991).

Whereas the evolution of the magnitude of the invested budgets over time is well documented, much less is known on whether, and to what extent, their effectiveness varies across the business cycle. We therefore investigate how this effectiveness may evolve for two important and highly visible marketing mix instruments, i.e. advertising and price.

Advertising effectiveness, on the one hand, could gain from economic downturns, as the overall advertising spending will be lower, thus reducing clutter (e.g. Danaher et al., 2008). Reduced advertising spending, moreover, may result in (temporary) increases in advertising elasticity as it has been shown that advertising has diminishing returns to scale and that companies show a tendency to overspend on advertising (Tellis, 2007). Advertising effectiveness, on the other hand, may as well suffer from economic downturns. Consumers refrain from spending as their disposable incomes may be lowered. Their willingness to buy, in addition, is likely to be reduced as well (Katona, 1975) as they easily loose trust during such circumstances (e.g. Shea, 1995; Gale, 1996; Bowman et al., 1999). In their buying decisions, in addition, they will focus more on functional relative to hedonic aspects like e.g. brand image, built by advertising (e.g. Ang et al., 2000). What the net effect of economic contractions on advertising effectiveness will be, is consequently hard to predict.

Price sensitivity, according to common sense, can only increase during economic downturns (see e.g. Block, 1977). During economic sour times, consumers become more rational in their buying behavior, looking for the best buy at the best price. They compare more, are more price aware (Estelami et al., 2001) and appreciate price cuts more (Quelch, 2008). Price sensitivity, in addition, is also likely to increase due to the actions of firms themselves. To undercut the competition, firms may offer more frequent or deeper price discounts, training consumers to pay even closer attention to price. However, even though we have good indications on the direction in which price sensitivity will evolve, nothing is known on the extent of the increase during contractions.

By investigating how the effectiveness of these two marketing mix instruments evolves, we are able to answer the call for clarity from managers on which strategies are most useful during economic downswings. We not just quantify these effects, but examine as well how they may be different for different types of products. Proper knowledge on the effectiveness evolution not only enables firms to adjust their budgets according to the relative effectiveness of the different marketing mix instruments, but also enables them to avoid so-called double jeopardy situations. In such situations, firms economize on investments in certain instruments, without knowing that the effectiveness of those instruments has actually decreased, resulting in even lower effects than anticipated when decreasing the budgets. The results of our study, in turn, give indications on optimal budgeting strategies for advertising and pricing across the business cycle.

II

UNDERSTANDING THE TIMING AND MAGNITUDE OF ADVERTISING SPENDING PATTERNS

Abstract

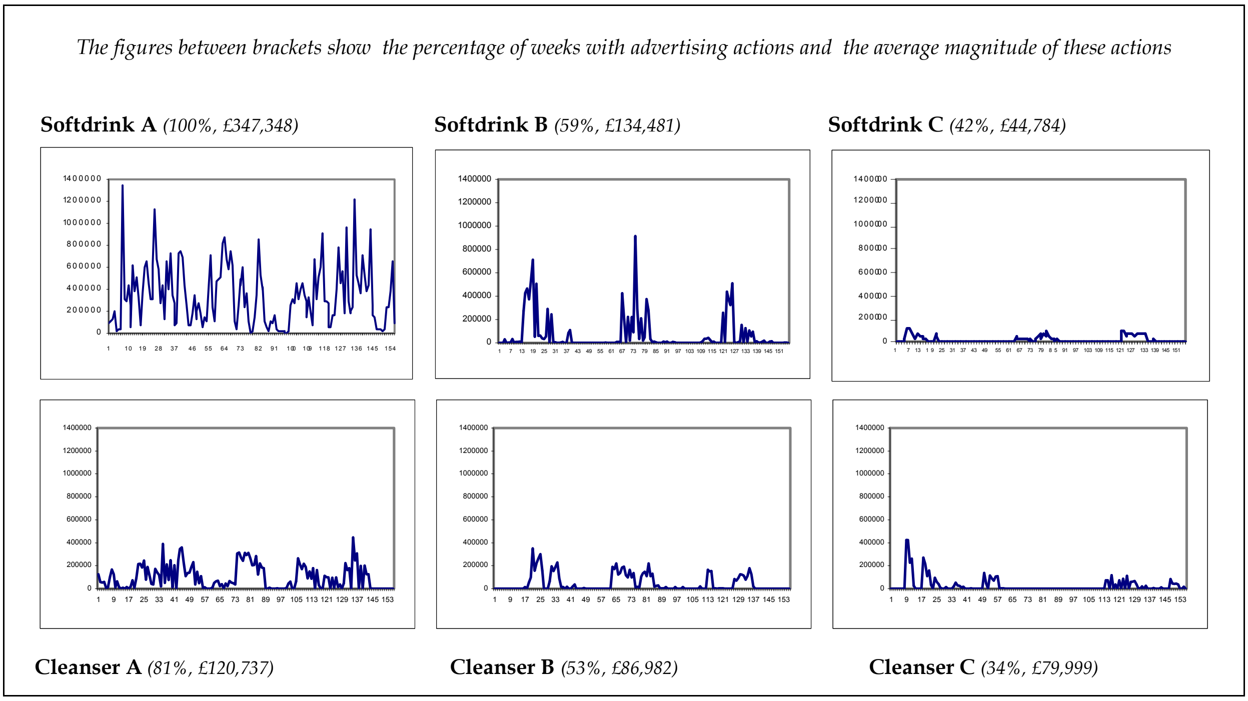
Notwithstanding the fact that advertising is one of the most used marketing tools, little is known about what is driving (i) the *timing* and (ii) the *magnitude* of advertising actions. Building on normative theory, a parsimonious model that captures this dual investment process is developed. We explain advertising spending patterns as observed in the market, and investigate the impact of company, competitive, and category-related factors on these decisions, thereby introducing the novel concept of Ad-sensor. Analyses are based on a unique combination of (i) weekly advertising data on 748 CPG brands in 129 product categories in the UK, (ii) household panel purchase data, and (iii) data on new product introductions. The analyzed brands include both large and small brands, both frequent and infrequent advertisers, thus providing a more complete and correct overview of the market. The results show that advertising spending patterns can be explained as real-life applications of the normative literature, in which advertising and advertising goodwill management are embedded in dynamic (s,S) inventory systems. Adstock and Ad-sensor show a positive effect on both timing and magnitude decision. Competitive reasoning is found to have little to no effect on advertising decisions, whereas category-related factors do show an impact. The extent to which campaigning strategies are more or less the outcome of advertising goodwill management systems, however, varies across brands as a function of their relative size and advertising frequency.

II.1. INTRODUCTION

Advertising is one of the most important marketing instruments. For example, in 2006, US adspend totaled \$285.1 billion, representing 2.2% of the country's GDP. Companies as Procter & Gamble and AT&T spend billions of dollars per year on advertising (Advertising Age, 2007). Given its prominent position, it should come as no surprise that advertising, and the way it affects people's decisions, has been the subject of an extensive body of prior research (see e.g. Tellis and Ambler 2007 for a recent review). The main focus of these studies was on the quantification of advertising's *effectiveness*. Studies explaining observed advertising *spending patterns*, in contrast, have received much less attention. Still, insights into why brands start/stop advertising are very relevant to advertising media and advertisers alike. The former will benefit from a profound understanding of the purchase behavior of their customers, i.e. the spending patterns of advertising brands. Advertisers, in turn, are interested in accurate predictions on the expected timing and size of their competitors' spending in order to gauge the extent of competitive interference they may expect (cfr. Danaher et al., 2008).

As shown in Figure II.1, considerable variation exists along both the timing and size dimension. The first three panels exhibit the weekly advertising expenditures for three soft-drink brands in the UK. Brand A is a frequent and heavy advertiser (100% of the time, average spending of £347,348 per week), while brand C is situated at the other end of the spectrum. It engages only occasionally in advertising actions (42% of the time), and when doing so, spends only small amounts (£44,784 on average). Brand B takes an intermediate position: it advertises less often than brand A (59% of the time), but spends a larger amount on these sparse actions than C (£134,481 on average). The bottom panels of Figure II.1 depict three brands in the UK cleanser market. Also in that market, considerable variability is observed in both the timing and the size dimension. Moreover, the absolute spending level appears to be considerably lower than in the soft-drink market. What is driving this over-time variation within a given brand? Why do we find such substantial differences across brands? Or across industries?

Figure II.1. Weekly advertising for three brands in the UK soft drink and cleanser markets



Some features of these observed patterns may have emerged as the result of applying the guidelines of a series of *normative* studies which have shown that, in most instances, pulsed advertising is an optimal strategy (e.g. Mahajan and Muller, 1986; Mesak, 1992; Park and Hahn, 1991; Villas-Boas, 1993; Naik et al.,1998). These studies, however, although insightful on the optimality of pulsed over even spending, remain vague on some crucial implementation issues, including (i) how often to advertise, (ii) how many weeks an advertising pulse or campaign should last, and (iii) how much should be spent. Moreover, (iv) they do not provide insights on the observed behavioral differences between brands and categories. As such, and differing from our study, their objective is not to explain the variation found in observed behavior. Such real world behavior, in contrast, was the focus of a body of *empirical* studies (e.g. Metwally, 1978; Jones, 1990; Hanssens, 1980a+b; Chandy et al., 2001; Steenkamp et al., 2005). These studies manage to capture and explain very well the behavior under examination, but are weaker in the theoretical foundations of their explanations, thus almost being the opposite of the normative studies.

We build on the normative literature, and develop a framework which allows us to describe and understand the advertising behavior as observed in the market, and this along two dimensions: (i) the *timing* of advertising actions (i.e. whether or not to advertise), and (ii) the *magnitude* of these actions. We subsequently relate observed differential behavior across brands to the size of the brands, and the experience they have in advertising.

We begin with an overview of the relevant literature (Section II.2). We subsequently present our conceptual framework, and introduce the core concepts of this study (Section II.3). We describe our econometric model (Section II.4), and give some initial insights in our data (Section II.5). We then present our empirical results (Section II.6), and conclude with a discussion of the key managerial insights and some areas for future research (Section II.7).

II.2. RELEVANT LITERATURE

The current paper can be positioned against two research streams: (i) normative studies on optimal advertising behavior, (ii) empirical studies on advertising and its effectiveness.

Normative literature

Over the past decades, the preponderance of the prescriptions from normative studies on the optimal timing of advertising has shifted from constant advertising schedules (Zielske, 1959; Sasieni, 1971; 1989) to pulsing advertising schedules (e.g. Mahajan and Muller, 1986) as more and more real-world effects were included in the analyses. For example, Katz (1980) introduced learning and forgetting effects, while Mesak (1992) and Naik et al. (1998) added, respectively, wear-out effects and quality restoration. Park and Hahn (1991), Villas-Boas (1993) and Dubé et al. (2005), in turn, extended the analyses to competitive settings. In most instances, pulsed advertising is now considered to be the optimal strategy for firms. Whereas pulsing is used as a generic term describing advertising schedules alternating high and low levels of advertising, flighting (e.g. Katz, 1980) is more strict in its definition as it refers to alternation between high and zero levels of advertising. As such, it is an extreme case of pulsing. Finally, the concept of campaigning (Doganoglu and Klapper, 2006) was introduced to describe the fact that advertising pulses are often not one-time spikes, but regularly last several weeks.

Pulsing strategies appear to be frequently applied by managers (Feinberg, 1992). Recently, Dubé et al. (2005) found evidence that the observed behavior in the US Frozen Entrée category could be explained as a pulsing strategy based on a dynamic competitive game. Doganoglu and Klapper (2006), covering the German Detergent Market, found similar support for the application of the normative guidelines in the real world decisions they studied. Finally, such patterns are also widely present in our own dataset (cfr. figure II.1), in which only 6 of the 748 included brands advertise permanently, thereby alternating between high and low levels of advertising.

However, in contrast with their general agreement on the optimality of pulsed advertising strategies, these normative studies provide less clarity on a number of issues related to the actual implementation of the advocated strategies. Analysis of real world advertising spending patterns indeed showed that, although pulsing strategies are often encountered, large differences are observed both within and between brands in (i) the actual timing of advertising campaigns, (ii) the number of weeks such campaigns last, and (iii) the monetary value of campaigns. Overall, very few normative studies go into that level of detail, and three limitations of these studies thus appear. First, these studies mainly focus on the timing of advertising actions within campaigns, thereby leaving especially decisions on the magnitude of these actions uncovered. Second, they provide guidelines for a single brand, thereby ignoring differences in individual brands' advertising preferences as well as factors that may systematically affect advertising decisions across different brands and categories. Finally, as a corollary of this single-brand focus, only very few studies allow advertising decisions to be correlated with the decisions of other brands (Park and Hahn, 1991; Villas-Boas, 1993; Dubé et al., 2005).

Empirical literature

In a wide series of econometric studies on advertising, measuring the *effectiveness of advertising* takes a central position. Performance was treated as a function of advertising expenditures in so-called single equation models (e.g. Lambin, 1969; 1975). These models treated advertising as exogenous, without investigating how spending patterns were formed. This exogeneity assumption was relaxed in subsequent simultaneous equation models, starting with Bass (1969) and including work by Bass and Parsons (1969) and Hanssens (1980a), as in more recent VAR models (Dekimpe and Hanssens, 1995; 1999). The latter not only allow for feedback effects (when past own performance helps explain current spending), but also for *competitive interactions*. A recent study in this field is Steenkamp et al. (2005), who used vector-autoregressive models to study advertising reaction strategies in 442 packaged goods categories.

A major strength of these studies is that they, in contrast to the normative studies, look further than the explanation of the behavior of just one brand, and try to explain patterns across brands and categories. However, this body of research shares three important limitations. First of all, the theoretical background in these studies is often rather limited. Often, observed patterns are explained without a concise and consistent theoretical framework grounded in the normative literature. Second, although advertising expenditures are no longer treated as exogenous, no distinction is made between the decisions to advertise or not (timing), and how much to spend when advertising (magnitude), even though the factors that drive both decisions could (partly) be different or have different weights. Finally, most (if not all) of these studies show a bias towards large and frequently acting brands. This is due to the fact that most time-series techniques have problems with large numbers of zeros and irregular patterns (e.g. in advertising spending), as is often the case with smaller brands. Steenkamp et al. (2005), for example, limited themselves to those top-3 brands in each category that also had an average share larger than 5%, and that advertised at least more than 12% of the time (25 out of 208 weeks). Zanutto and Bradlow (2006) showed that such data pruning may bias the overall inferences, as the included brands are only representative for a small subset of all brands in the market. Hence, the empirical generalizations derived in these studies may only be valid for that specific subset.

Our study

We build upon the insights of the existing normative literature on optimal advertising scheduling by including campaigning in our framework. Two crucial elements in our work are the concepts of Adstock and Ad-sensor, capturing the campaigning state dependence of brands and their dynamic pulsing behavior, respectively.

The definition of campaigning implies two basic conditions. First of all, campaigns are defined as prolonged periods of advertising, alternated by periods without advertising. Once advertising has begun, it will be continued for some time. This state dependence will be captured by the Adstock concept, a concept which is widely known and used in advertising research (e.g. Broadbent, 1984; Hanssens et al., 2001). The probability of a new advertising action will be higher if a brand was also advertising in the previous weeks, which has resulted in higher Adstock. Conversely, the probability of no new advertising action will be higher if the brand was not advertising in the previous weeks. During these weeks, Adstock was depleting, resulting in a lower Adstock level. The second condition holds that, at a certain moment in time, one has to start a new campaign, i.e. start advertising. Conversely, at a certain moment in time, a campaign will end, and one has to stop advertising. Managers want to keep their Adstock above a certain level. As soon as the Adstock, built by previous campaigns, has depreciated to that level, one will start advertising. Similarly, one is likely to stop advertising once a desired (higher) level has been reached again. This advertising reasoning shows close resemblance to so-called (s,S) inventory management systems. Such systems keep the stock of a certain item between a minimum level s and a maximum level S, by repurchasing if the stock becomes too small, up to the desired maximum level. Although very popular and widely used in logistics (e.g. Silver et al., 1998), applications in advertising research are rather scarce (Zufryden, 1973; Doganoglu and Klapper, 2006). To capture these dynamics, we introduce the Ad-sensor concept. As Ad-sensor and Adstock each capture a distinct feature of advertising campaigns, the analysis of both concepts provides us with a clear and concise view of such campaigning behavior.

As such, we build a parsimonious and flexible model which captures in a straightforward way how observed advertising spending patterns could result from dynamic advertising adjustment strategies. We address limitations of previous research by incorporating four main challenges in our model specification: (i) we allow for differential processes driving the timing and magnitude decisions, (ii) we accommodate heterogeneous preferences and behavior across brands, (iii) we examine the effect of moderating variables across brands and categories, and (iv) we accommodate correlations between the brands decisions within the same category.

Our study, in addition, is unique in its empirical scope, covering advertising decisions on a weekly basis for 748 brands in 129 CPG categories. We include all brands in these categories that advertise in our study, regardless of their advertising intensity (provided that they advertise at least once, otherwise the issue becomes moot) and their Brand market share. An illustration of the relative importance of this issue can be found in figure II.2. This figure depicts the consequences of the application of the decisions rules as used in Steenkamp et al. (2005) to our dataset. We categorize all brands according to their compliance (Y/N) with the size (top 3, minimum 5% market share) and frequency limitation (minimum advertising frequency of 12%). For each block we report the Number of brands (*N*); their Combined share of advertising in our dataset; Mean market share; Mean combined market share; Mean advertising share in their category; and the Mean number of advertising weeks.

If we only include the brands in our empirical dataset that fulfill both requirements, we would cover only 63.9% of all advertising expenditures. Brands would have an average market share of 18.4%, and an advertising share of 41.2%, advertising on average 82 out of 156 weeks. However, these brands, on average, account for only 32.7% of the total market, covering, on average, between 0.6% and 99% of category advertising expenditures as included in our dataset.

Figure II.2. Application of the Steenkamp et al. (2005) data pruning rules to our dataset

	Advertising Frequency > 12%	**Advertising Frequency ≤ 12%**
Top 3 AND Market share > 5%	N = 151 Combined share of advertising = 63.9% Mean market share = 18.4% Mean combined market share = 32.7% Mean advertising share in category = 41.2% Mean number of advertising weeks = 82	N = 71 Combined share of advertising = 0.8% Mean market share = 17.7% Mean combined market share = 20.3% Mean advertising share in category = 40.6% Mean number of advertising weeks = 7
Not Top 3 OR Market share ≤ 5%	N = 229 Combined share of advertising = 33.7% Mean market share = 2.1% Mean combined market share = 7.7% Mean advertising share in category = 11.5% Mean number of advertising weeks = 57	N = 297 Combined share of advertising = 1.6% Mean market share = 1.0% Mean combined market share = 3.2% Mean advertising share in category = 3.9% Mean number of advertising weeks = 6

Limiting the number of included brands would clearly lead to the omission of a major part of the observed advertising actions and expenditures from our analyses. Relaxing the aforementioned requirements hence appears recommended. Relaxing the size limitation would enable us to cover over 98% of all advertising expenditures. In addition, although infrequent advertisers represent only a very small percentage of advertising *expenditures*, they still account for almost 50% of the advertising *brands*, and nearly 10% of all advertising *actions*. Understanding how their behavior may differ from more frequently acting brands is consequently warranted if we want to understand advertising as we observe it in the market. The unique dataset we thus obtain, allows us to formulate a set of insightful empirical generalizations on the timing and magnitude of observed advertising patterns.

II.3. DRIVERS OF ADVERTISING INVESTMENT DECISIONS

Advertising decisions can be seen as a multiple decision process. Two key decisions which have to be taken, are *when* to advertise, and *how much* to spend (Tellis, 2004 p. 72; Danaher, 2007 p. 645; Danaher et al., 2008). This dual advertising decision is treated as an investment decision process, which is in line with the growing stream of literature claiming that marketing expenditures are more and more considered to be investments (Srivastava et al., 1998). At each point in time, the brand therefore chooses (i) whether or not to advertise (*timing*), and, (ii) conditional upon this decision, how much to spend (*magnitude*) (e.g. Bar-Ilan and Strange, 1999).

Adstock

Central to our model are the concepts of Adstock and Ad-sensor, which in itself is also derived from Adstock. These concepts each capture a crucial aspect of advertising investments. The tendency to concentrate advertising investments in longer pulses or campaigns of continued advertising, as we will show, is captured by our Adstock variable (Broadbent (1984). Ad-sensor, reflecting the dynamics in Adstock, is subsequently introduced as a feedback variable mimicking the brand's decision rule to start and stop advertising campaigns. This basic advertising investment decision process is depicted in figure II.3.

Figure II.3. Basic advertising decision process

The Adstock concept was originally developed to assess the dynamic effects of advertising. It rests on the assumption that advertising helps to build a stock of advertising goodwill (Broadbent, 1984). In the absence of further advertising spending, however, this Adstock decays at a constant rate (see e.g. Dekimpe and Hanssens, 2007). In the past, it has been used in studies on e.g. advertising awareness (Brown, 1986), television advertising effectiveness (Tellis and Weiss, 1995), television scheduling (Broadbent et al., 1997; Ephron and McDonald, 2002), trial of new products (Steenkamp and Gielens, 2003), product-harm crises (Cleeren et al., 2008) and competitive advertising interference (Danaher et al., 2008). In line with these studies, we follow the definition by Broadbent (1984) and operationalize Adstock of brand b as:

(II.1) $$Adstock_{b,t} = (1-\lambda_b)Advertising_{b,t} + \lambda_b Adstock_{b,t-1}$$

Advertising is often scheduled in campaigns of several consecutive weeks, followed by zero advertising during a number of weeks. The likelihood of a brand advertising in week t will consequently be higher when it was also advertising in the weeks before. During this period, Adstock will be built by means of advertising actions. So, a brand which is in a campaign keeps advertising when its Adstock is at relatively high levels. Conversely, the likelihood of a brand not advertising in week t will be lower when it was not advertising in the previous weeks. During such periods, Adstock will be considerably lower as it decays when no new advertising investments are made. We therefore expect a positive effect of Adstock on the likelihood of a new advertising action in week t.

Conditional upon their decision to advertise, brands still have to determine the amount they will spend on their action. As decision making processes are often characterized by a strong preference for the status quo (e.g. Samuelson and Zeckhauser, 1988), previous behavior is a particularly good predictor of new actions (e.g. Nijs et al., 2007). Higher advertising levels during the previous weeks of a campaign are therefore likely to be followed by higher levels in a subsequent action, provided that the brand chooses to advertise. Higher previous advertising expenditures during a campaign, in turn, are reflected in relatively higher Adstock levels, whereas lower advertising levels will have resulted in relatively lower Adstock levels. We therefore can expect that brands, conditional on the decision to advertise, will spend more on such new actions when their Adstock level is higher.

Together, these two effects, both in timing and magnitude of advertising actions, show how Adstock captures the state dependence of brands in their advertising decisions.

Ad-sensor

Although Adstock provides a better understanding of the campaigning state dependencies, it is less insightful on why brands would start or stop an advertising campaign. What triggers the launch of new campaigns? Why and when do they end? Answers to these questions can be found by analyzing the goals of advertising investments. By means of advertising, brands build advertising goodwill among consumers. This goodwill is expected to translate into sales, and should consequently not fall below a certain level. If this, however, would be the case, new advertising investments become necessary to preserve and strengthen sales. At that moment, a new campaign will be launched. The ultimate goal of any brand would be to achieve unlimited goodwill. However, advertising budgets are not unlimited. We therefore assume that a specific target level of goodwill will be determined for each campaign, the level of which is unknown to us. In the beginning of a campaign, when goodwill build-up has just started, incentives to stop will be rather small. The closer to the target level, however, the lower will be the need to continue investing. In addition, once it has been reached, there is a clear incentive to stop investing. The pressure a brand feels to start a campaign as soon as its goodwill among consumers becomes too low, and to stop that same campaign when the desired (higher) goodwill level is reached, is the essence of our Ad-sensor concept. As such, it provides extra information on campaigning behavior in addition to the information as provided by Adstock, without making the latter superfluous, as these two concepts cover two different processes which are at play.

We define our Ad-sensor by integrating the Adstock concept in an (s,S) stock replenishment system. As such, s represents the minimum Adstock level a brand wants to maintain, whereas S is the (higher) target level. The implicit goal of such (s,S) systems is hence to maintain the stock between the two levels. These levels are known to the brand manager, but unknown to the researcher. In addition, managers can apply dynamic strategies in their choice of these minimum and maximum levels, thus allowing for different levels in different campaigns. We therefore consider the observed minimum and maximum levels as the actual outcomes of managers' utility maximization calculi.

To model this (s,S) behavior, we first consider what happens when the Adstock of brand b falls below the minimum desired level. At that moment, the brand should start advertising again. The brand will launch a new campaign, and will continue to invest in advertising until the target is reached. At that maximum, the first derivative of Adstock to time is zero, at least in continuous time. Since we are using discrete time observations, however, at time t the researcher can only observe up to time t-1, so the first order condition is equivalent to:

(II.2) $$\frac{\Delta Adstock_{b,t-1}}{\Delta t} = 0 \, .$$

this becomes:

(II.3) $$\frac{Adstock_{b,t-1} - Adstock_{b,t-2}}{\Delta t} = 0$$

(II.4) $$\Leftrightarrow Adstock_{b,t-1} - Adstock_{b,t-2} = 0 \, .$$

Given our additive Adstock function, this is satisfied if:

(II.5) $$(1-\lambda_b)Advert_{b,t-1} + \lambda_b Adstock_{b,t-2} - Adstock_{b,t-2} = 0$$

(II.6) $$\Leftrightarrow (1-\lambda_b)Advert_{b,t-1} = (1-\lambda_b)Adstock_{b,t-2}$$

(II.7) $$\Leftrightarrow Advert_{b,t-1} = Adstock_{b,t-2}$$

The second-order condition for a maximum requires that in the period before the maximum, t-1, Adstock is still increasing, which requires that $Advert_{b,t-2} > Adstock_{b,t-3}$. Based on these observations, we define our Ad-sensor variable as the difference between Adstock in time *t*-1 and Adstock in *t*-2:

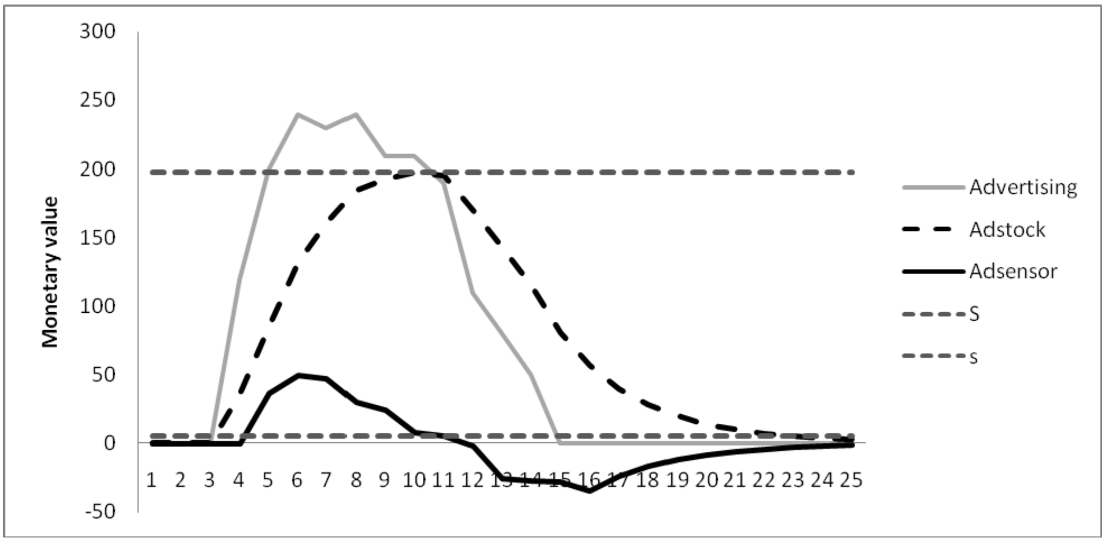
(II.8) $$Adsensor_{b,t} = Adstock_{b,t-1} - Adstock_{b,t-2}$$

The full mathematical derivation of Ad-sensor is given in appendix A. As such, the Ad-sensor allows us to capture the evolution of a brand's Adstock, and the associated pressure to advertise. During the build-up of Adstock, Ad-sensor will have positive values. Over time, as Adstock increases, these values start to decrease. Once the target maximum Adstock level S was reached, Ad-sensor becomes negative, a clear incentive to stop advertising. Over time, Adstock depletes, and Ad-sensor increases again, implying an increasing pressure for the brand to advertise again.

To provide better insights in the functioning of this system, we simulate a series of advertising actions. In our simulation, we impose values on the carry-over parameter λ, which is used to calculate Adstock and consequently Ad-sensor, and the minimum and maximum Adstock levels s and S. In practice, however, we estimate all parameters based on the observed advertising patterns. The numerical build-up of this example is included in appendix B. The evolution of the associated Ad-sensor is represented in figure II.4. The solid grey line represents the advertising expenditures, the dotted black line the created Adstock and the solid black line the Ad-sensor. As indicated by equation (II.8), the latter represents the recent change in Adstock due to advertising investments.

In week 4, the brand launches a new campaign, as Adstock has fallen below the allowed minimum level s. As a corollary of our Adstock definition, Adstock will increase as long as the advertising investments are larger than the previous Adstock level (see appendix A). The first investments start building Adstock, but at the same time as well increase the pressure not to stop the campaign prematurely (captured by the Ad-sensor), as the desired level S is still far away. By period 6, the Adstock level is increasingly approaching the advertising level, and increases in Adstock start becoming smaller. Gradually, the brand is approaching the target Adstock level S. This is also reflected in the Ad-sensor, which slowly starts to decay from period 7 on. Stopping becomes less harmful, as the target level is getting closer.

Figure II.4. Advertising, Adstock and Ad-sensor



In week 10, the maximum (desired) Adstock level has been reached. By week 11, Ad-stock starts to decay. Ad-sensor, in turn, becomes strongly negative in the next period: the target of the campaign was attained, continued investments make little sense. However, still some smaller amounts of advertising are typically found at the end of advertising campaigns. These are often due to so-called make-goods (see e.g. Doganoglu and Klapper, 2006), smaller actions often added at the end of campaigns in order to compensate for lost opportunities during the campaign itself. Over time, Adstock depletes at a constant rate λ (see equation II.1), but not in constant absolute terms. When Adstock levels are still high, depletion will be large in absolute terms, causing strong negative Ad-sensor values. Over time, the Adstock level becomes smaller, and depletion will be smaller in absolute terms. This results in a gradual increase of the Ad-sensor.

In sum: the Ad-sensor variable is essentially a feedback variable mimicking the brand's decision rule to start and stop advertising. We thus expect a positive effect of the Ad-sensor on the timing decision (yes or no). In addition, a similar effect is hypothesized for the magnitude decision (given timing). A wider gap between the actual and the target Adstock level requires stronger efforts to rapidly bridge this gap. As the brand gets closer to the target level, however, this pressure becomes smaller, as the gap has become much smaller. Beyond the point in time at which the target level was reached, the relevance of continued spending can be questioned. The Ad-sensor tells brands that, if they still would be spending on advertising actions, it should at least be small amounts.

Moderating factors of Adstock and Ad-sensor

The combination of Adstock and Ad-sensor creates a new model for the analysis of advertising decisions. A subsequent investigation of the general applicability of this model across a large set of brands is hence asked for. However, the extent to which Adstock is managed between s and S may differ across brands. In this paper, we focus on two important brand characteristics: *Brand market share* and *Advertising frequency*. The motivation for this choice is threefold. First of all, both factors have commonly been used in the past as a basis for data selection rules (e.g. Steenkamp et al., 2005). Brands typically included in previous studies on the basis of such selection rules, however, are not representative for the market as a whole (Slotegraaf and Pauwels, 2008), and inferences based on these subsets could be biased (Zanutto and Bradlow, 2006). As we include all types of brands, understanding to what extent behavior may differ for types of brands which were previously excluded from analyses is essential, and can in addition provide insights on the extent to which data pruning rules could have altered our findings. In addition, two other motivations explain our choice. Brand market share has emerged from previous research as a key characteristic in advertising decisions (e.g. Patti and

Blasko, 1981; Lynch and Hooley, 1990). Advertising decision making and its outcome will depend on the market share a brand has and wants to maintain. Advertising frequency, in turn, may create learning effects. An examination of the effect of advertising frequency consequently helps us to understand if, and to what extent, more experienced brands have gained a relative advantage over time in managing their Adstock.

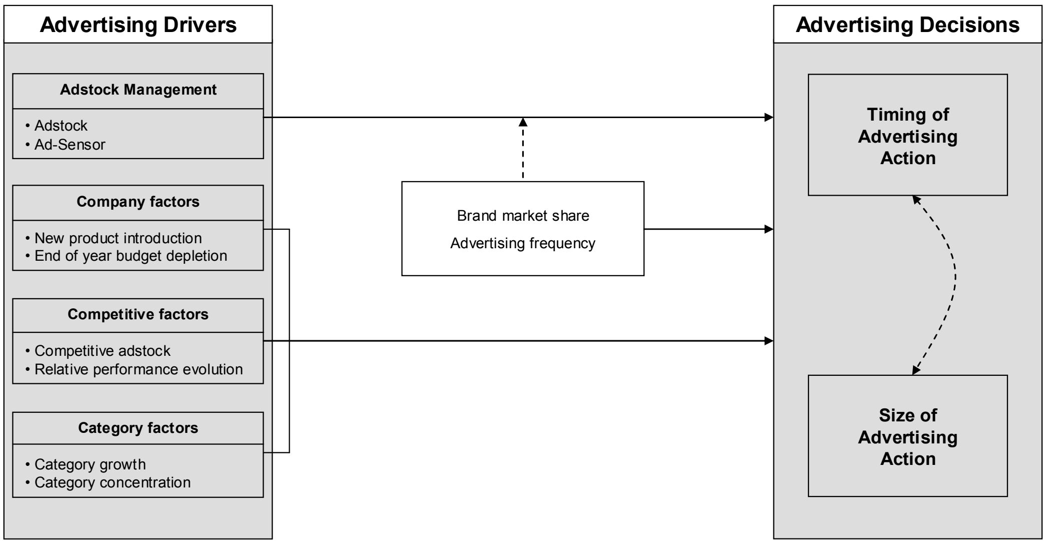
Larger brands have more means at their disposal, and marketing budgets, moreover, are often determined on a percentage of sales basis (Allenby and Hanssens, 2005). This will affect the advertising decision process in two ways. These brands can reserve larger budgets for marketing research compared to their smaller counterparts. They thus can be expected to be better informed on how their advertising goodwill level is evolving, and can consequently better react to it. We therefore expect a positive effect of *Brand market share* on the effect of Ad-sensor in both decisions. In addition, their larger budgets allow them to pursue longer and more intense advertising campaigns. The state dependence effect as implied by the Adstock will consequently be higher for such brands.

Experience enables brands to adapt their organizations and processes in order to perform optimally. The advertising decision process is no exception to this. More experienced brands have become more efficient through learning effects and have established effective advertising decision processes. On the organizational level, these decision processes tend to stay very similar over time (Frederickson and Iaquinto, 1989), as organizations have to be reliable, accountable and reproducible (Boeker, 1988). What has proven to be effective, will be continued. A consistent closer monitoring of the advertising goodwill evolution as well as reactance to it can consequently be expected. We therefore expect the effect of Ad-sensor to be positively affected by *Advertising frequency*. This experience, built by more intense advertising strategies in the past, moreover, will as well enable brands to better pursue longer and more intense advertising campaigns. The effect of Adstock is consequently expected to be stronger for more experienced brands.

Covariates

However, it is unlikely that advertising decisions are only influenced by brands' own internal advertising reasoning. Three main sets of factors are commonly considered: (i) Company factors, (ii) Competitive factors, and (iii) Category or marketplace factors (Montgomery et al., 2005). Figure II.5 summarizes this extended advertising decision process.

Figure II.5. Extended advertising decision process



First of all, brands will look at themselves. As advertising theory tells that *New product introductions* should be combined with more intense advertising campaigns (e.g. Rossiter and Percy, 1997; Kotler and Armstrong, 2004), especially because advertising has shown to be more effective for new products (Lodish et al., 1995), we can expect a positive effect of such introductions on the advertising decisions, resulting in a higher likelihood of advertising and higher actual expenditures. Overall, however, advertising budgets are often set on a yearly basis (e.g. Farris and West, 2007). In the course of the year, these budgets get depleted, most often faster than expected, sometimes slower, creating relative shortage or slack resources by the end of the year respectively. Given the common knowledge that having money leads to spending it, we expect brands to spend their budgets relatively faster in the beginning of the year. This leaves them with relatively fewer means at the end, and thus a negative impact of an *End of year* dummy on the advertising decisions, resulting in fewer and smaller advertising actions, is hypothesized.

Next to themselves, brands will monitor their competitors and their own performance relative to the latter. *Competitive adstock* captures the likelihood of competitive advertising campaigns. The effect of this factor on the decision outcome is not clear a priori, as arguments in both directions can be found, with brands clearly reacting on each other (e.g. Metwally, 1978; Chen and MacMillan, 1992), or trying to avoid competitive clutter (Danaher et al., 2008). In addition, brands frequently make decisions in order to perform well relative to their competitors, on e.g. market share (e.g. Metwally, 1978; Armstrong and Collopy, 1996). However, as budgets are often set as a percentage of past sales (see e.g. Allenby and Hanssens, 2005), a negative *Relative performance evolution* versus competitors as expressed by a decrease in market share may at the same time create a stronger urge to react and lower the ability to react. Here as well, the effect on the advertising decisions is not clear a priori.

Finally, brands are looking at the markets they are operating in. High *Category growth* not only engenders larger current profits and hence marketing budgets, it can also be regarded as an indicator of potential future profits, leading companies to defend their positions in such categories even more fiercely (Gatignon et al., 1990). At the same time, however, if category growth is near zero, competitive actions can become a zero-sum game. Hence, such categories can be characterized by intense competition, also with advertising, to protect sales volumes (Aaker and Day, 1986). Given the well-known detrimental impact of such strategies on the profits of the brands, we hypothesize that the indicator-of-future-profit effect will be stronger than the zero-sum effect, leading to a positive effect of category growth on the advertising decisions. Categories with higher *Category concentration* are more open to collusive behavior, leading to lower competitive interactions (e.g. Steenkamp et al., 2005), and thus likely as well to lower advertising spending. We therefore expect to find a negative effect of concentration on the advertising decisions.

The conceptual framework presented here is summarized in figure II.5. We investigate the ability of Adstock and Ad-sensor to explain advertising decisions, test the influence of moderating factors Brand market share and Advertising frequency, while controlling for an extensive set of other variables. We relate our results further to the literature when reporting our empirical findings.

II.4. MODEL DEVELOPMENT

Our conceptual framework implies four modeling requirements. First, we need to model both the timing (yes/no) and spending decision (monetary value), while allowing for different response parameters for both decisions[1]. Second, these response parameters are allowed to vary across brands. Third, we need to accommodate the effects of the moderating variables, preferably in a simultaneous estimation step for maximal statistical efficiency. Fourth, the decisions of when and how much to spend may be interrelated between brands within a category, and hence we need to specify a full error covariance structure.

To meet these requirements we link the drivers to the two decision variables (i.e. timing and magnitude) through a new multivariate Hierarchical Tobit-II model, which extends the models of Fox et al. (2004) and Van Heerde et al. (2008) as these models do not comply with all four requirements[2]. In the subsequent exposition, c refers to category (c=1,…,C) and b to brand (b=1,…,B_c).

[1] A similar framework, investigating timing and magnitude of capital stock investments, was introduced by Bar-Ilan and Strange (1999). The authors allowed the company to decide on both when and how much to invest, thereby going beyond existing literature that focused on either timing or intensity of investments. Bowman et al. (2000) extended this reasoning to the choice and level of use of international service providers. Dekimpe et al. (2000), in turn, introduced a similar dual but also more sequential reasoning to international new product adoption processes. Finally, Gielens and Dekimpe (2007) applied a resembling framework to the entry strategy of retail firms into transition economies.

[2] These models do not allow for effects of moderating variables on the response parameters. In addition, in the work of Fox et al. (2004) no full error covariance structure is specified across the two equations; error covariance structures are separated for incidence and timing.

Timing

An advertising decision in category *c* by brand *b* in week *t* (z_{cbt}) is described by a multivariate probit model:

$$z_{cbt} = \begin{cases} 1 \ \text{if} \ z^*_{cbt} > 0 \\ 0 \ \text{otherwise} \end{cases} \tag{II.9}$$

Previous work suggests analyzing the decisions at a weekly level. In general, less data aggregation provides more accurate results (Tellis and Franses, 2006). In addition, the managerial survey reported by Steenkamp et al. (2005) indicated that brands can react to events as fast as within one week, but generally not faster.

The latent variable z^*_{cbt}, describing the timing decision process of the brand, is modeled through a linear model:

$$\begin{aligned} z^*_{cbt} = {} & \zeta^{cb}_{1,0} + \zeta^{cb}_{1,1} Adstock_{cb,t-1} + \zeta^{cb}_{1,2} Ad-sensor_{cb,t} + \zeta^{cb}_{1,3} CompAdstock_{cb,t-1} \\ & + \zeta^{cb}_{1,4} PerfEvol_{cb,t-1} + \zeta^{cb}_{1,5} NPI_{cb,t} + \zeta^{cb}_{1,6} EOY_{cb,t} + \zeta^{cb}_{1,7} CatGrowth_{c,t-1} \\ & + \zeta^{cb}_{1,8} CatConc_{c,t-1} + \zeta^{cb}_{2,1} Holiday_t + \zeta^{cb}_{2,2} Qrtr1_t + \zeta^{cb}_{2,3} Qrtr2_t \\ & + \zeta^{cb}_{2,4} Qrtr3_t + \zeta^{cb}_{2,5} Trend_t + \mu_{cbt} \end{aligned} , \tag{II.10}$$

In equation (II.10) we first include a set of *time-varying* variables, i.e. Adstock and Ad-sensor and the covariates Competitive adstock, Relative performance evolution, New product introduction, End of year budget depletion, Category growth and Category concentration. In addition, we *control* for holidays, seasonality, and possible trending behavior. As advertising decisions for time t will be based on information available up to time t-1, we include 1 period lagged versions of most time-varying explanatory variables.

Amount spent

Conditional on the decision to advertise (z_{cbt} = 1), we model y_{cbt}, the natural logarithm of the amount spent on advertising by brand *b* in category *c* during week *t* as:

$$y_{cbt} = \omega_{1,0}^{cb} + \omega_{1,1}^{cb} Adstock_{cb,t-1} + \omega_{1,2}^{cb} Ad-sensor_{cb,t} + \omega_{1,3}^{cb} CompAdstock_{cb,t-1}$$
$$\text{(II.11)} \quad + \omega_{1,4}^{cb} PerfEvol_{cb,t-1} + \omega_{1,5}^{cb} NPI_{cb,t} + \omega_{1,6}^{cb} EOY_{cb,t} + \omega_{1,7}^{cb} CatGrowth_{c,t-1}$$
$$+ \omega_{1,8}^{cb} CatConc_{c,t-1} + \omega_{2,1}^{cb} Holiday_t + \omega_{2,2}^{cb} Qrtr1_t + \omega_{2,3}^{cb} Qrtr2_t$$
$$+ \omega_{2,4}^{cb} Qrtr3_t + \omega_{2,5}^{cb} Trend_t + \varepsilon_{cbt}$$

We include the same explanatory variables in the magnitude equation as in the timing equation. Although there is no specific requirement to have the same set in both equations, we include them in an exploratory way to investigate whether all factors have an effect in both decisions.

Moderating factors

In their specific baseline advertising preferences (the intercepts) and their reactions to their Adstock and Ad-sensor, brands may be guided by a number of own-company and category factors, as these may shape both the ability and the necessity to react. We therefore relate a subset of the response parameters $\boldsymbol{\zeta}_1^{cb}$ and $\boldsymbol{\omega}_1^{cb}$ to a set of moderator variables:

$$\text{(II.12)} \quad \zeta_{1,0}^{cb} = \overline{\zeta}_{1,0,0} + \overline{\zeta}_{1,0,1} BrandMarketShare_{cb} + \overline{\zeta}_{1,0,2} AdvFreq_{cb}$$
$$+ \overline{\zeta}_{1,0,3} Food_c + \overline{\zeta}_{1,0,4} Drinks_c + \overline{\zeta}_{1,0,5} Cosmetics_c + u_{1,0}^{cb}$$

$$\text{(II.13)} \quad \zeta_{1,i}^{cb} = \overline{\zeta}_{1,i,0} + \overline{\zeta}_{1,i,1} BrandMarketShare_{cb} + \overline{\zeta}_{1,i,2} AdvFreq_{cb} + u_{1,i}^{cb}, \quad for\ i = 1,2.$$

$$\text{(II.14)} \quad \omega_{1,0}^{cb} = \overline{\omega}_{1,0,0} + \overline{\omega}_{1,0,1} BrandMarketShare_{cb} + \overline{\omega}_{1,0,2} AdvFreq_{cb}$$
$$+ \overline{\omega}_{1,0,3} Food_c + \overline{\omega}_{1,0,4} Drinks_c + \overline{\omega}_{1,0,5} Cosmetics_c + e_{1,0}^{cb}$$

$$\text{(II.15)} \quad \omega_{1,i}^{cb} = \overline{\omega}_{1,i,0} + \overline{\omega}_{1,i,1} BrandMarketShare_{cb} + \overline{\omega}_{1,i,2} AdvFreq_{cb} + e_{1,i}^{cb}, \quad for\ i = 1,2.$$

The included moderator variables are *time-invariant* and allow us to measure the cross-sectional variance in baseline advertising preferences as expressed by the intercept included in (II.10)-(II.11). The categories included in our sample, can be categorized under four main product classes, i.e. Household Products, Food, Drinks and Cosmetics. We control for the preferences of these four product classes, using Household Products as reference category. In addition, we investigate the possible moderating effect Brand market share and Advertising frequency can have on both the baseline advertising preferences and the impact of Adstock and Ad-sensor on the advertising decisions. Mean-centering of both variables allows us to examine the effects of deviations relative to an 'average' brand. The effects of the covariates, captured by $\zeta_{1,i}^{cb}$ and $\omega_{1,i}^{cb}$ (for i = 3…8), are related to the hyperparameters $\overline{\zeta}_{1,i,0}$ and $\overline{\omega}_{1,i,0}$, and the brand-specific error terms $u_{1,i}^{cb}$ and $e_{1,i}^{cb}$.

Decisions by one brand on when and how much to advertise are likely to impact those of other brands. We therefore assume that the error vectors $\boldsymbol{\mu}_{ct} = (\mu_{c1t}, \ldots, \mu_{cB_ct})'$ and $\boldsymbol{\varepsilon}_{ct} = (\varepsilon_{c1t}, \ldots, \varepsilon_{cB_ct})'$ follow a joint multivariate normal distribution, with a full variance-covariance matrix: $(\boldsymbol{\varepsilon}_{ct}^{'}, \boldsymbol{\mu}_{ct}^{'})' \sim MVN(0, \boldsymbol{\Sigma}_c)$. Finally, unobserved drivers of model parameters may cause the error terms in (II.12) up to (II.15) to be correlated as well: $(\mathbf{e}_{cb}^{'}, \mathbf{u}_{cb}^{'})' \sim MVN(0, \boldsymbol{\Omega})$.

We estimate model (II.10)-(II.15) with Bayesian techniques, i.e., Gibbs sampling. The benefit of this approach over classical approaches is that it, at the same time, (i) accommodates the multivariate nature of our dependent variable, (ii) allows for full variance-covariance between all decisions by brands within the same category, and (iii) estimates the moderator effects simultaneously with the other parameters rather than in a two-step approach. An overview of this procedure is given in appendix C.

To operationalize the Adstock and Ad-sensor variables, we need to know the brand-specific carry-over parameter λ_b (see equation II.1). To estimate these carry-over parameters, we use the following traditional partial adjustment model (Hanssens et al., 2001 p147):

(II.16) $Sales_{b,t} = \alpha_b + \beta_b Adv_{b,t} + \lambda_b \ln Sales_{b,t-1} + \varepsilon_{b,t}$

Here as well, we use Gibbs sampling to obtain draws for λ_b. For more details, we refer to appendix D.

II.5. DATA DESCRIPTION

We estimate our model on 129 CPG categories in the UK. These categories cover nearly completely the assortment offered in a typical supermarket. An overview of the included product categories, along with the range of included brands, is given in table II.1.

Table II.1 Overview of included product types

Product Fields	Examples	No. of Categories	Range of Brands
Assorted Foods	Breakfast cereals, dry pasta, flour	23	1-11
Beverages	Brandy, mineral waters, softdrinks	20	1-27
Cakes	Oatcakes, crumpets pickelets and muffins	4	1-9
Candy	Cereal bars, countline chocolate, fruit bars	7	1-15
Canned/bottled foods	Canned fish, canned fruit	8	1-9
Care products	Deodorants, shampoo, toilet tissue	22	1-27
Cleaning products	Descalers, scouring powders, drain care	14	1-14
Dairy products	Butter, cream, yoghurt	7	1-11
Frozen foods	Frozen fish, frozen vegetables	4	2-6
Household supplies	Batteries, car freshener	3	1-9
Pet products	Dog food, cat litter	3	2-21
Taste enhancers	Mustard, vinegar, Worcester sauce	14	1-30
Total		*129*	*748*

Four years of weekly advertising spending data were obtained from NielsenMedia, from which we use one year (52 weeks) as initialization period, and three years (156 weeks) as estimation period. All brands that (i) advertised at least once during the estimation period, and (ii) were present in the market during the whole estimation period, were included. As such, both small and large brands were considered, as reflected in the range of their average (across the three years estimation period) market-shares, which varied from a low of 0.0002% to a high of

97.76%. We focused on national brands, as private labels have a very different positioning and advertising strategy (Kumar and Steenkamp, 2007). Still, private labels were considered in the derivation of certain covariates, as the concentration level in the industry or the national brands' market shares. These decision rules resulted in a sample of 748 brands. Even though the focus of the current paper is to study the spending pattern of brands that advertise, it is interesting to note that 1855 brands never advertised during the considered three years, even though they were in the market for the entire period.

Among the 748 brands that did advertise at least once, considerable variability exists in their advertising behavior, as was already indicated in figure II.2. First, the number of advertised weeks varies greatly. About one out of ten brands advertised only once, while a few brands (6 in total) advertised every week. However, the distribution is quite skewed, as nearly half of the brands advertised less than 10% of the time (see figure II.6).

Figure II.6. Advertising weeks

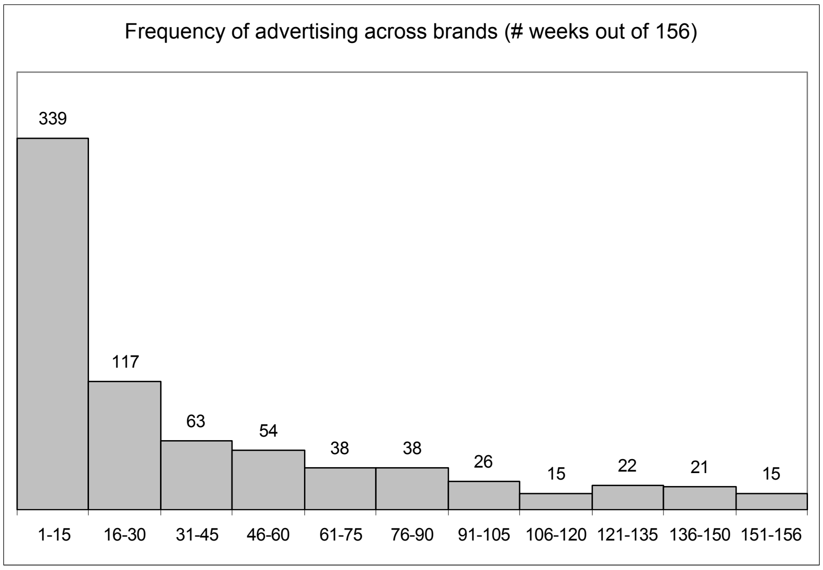


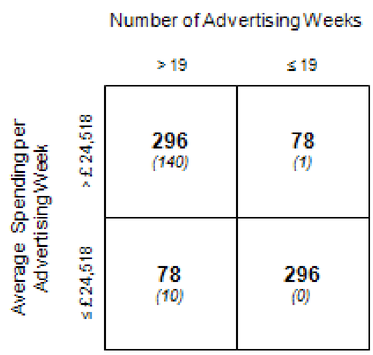
Table II.2 also provides evidence for the large variability in actual spending, even when conditioning on those weeks where a given brand advertises. Some brands typically spend large amounts (with an average level of £814,536 per week), while others spend only a limited amount per week (£19).

Table II.2. Advertising behavior of the included brands

	Range	Average	Standard deviation
Number of Advertising Weeks	1-156	37	42
Average Spending per Advertising Week (in £)	19-814,536	56,756	72,150

Combining both dimensions (using a median split on, respectively, the number of weeks of non-zero spending and the average value of such non-zero spending), we observe two main types of advertisers in Figure II.7: Heavy advertisers, who spend large amounts per week for multiple weeks; and Light advertisers, limiting themselves to fewer actions and smaller amounts.

Figure II.7. Brands in dataset classified by Number of Advertising Weeks vs Average Spending per Advertising Week, based on median split



Numbers between brackets show the number of brands which comply with the Steenkamp et al. (2005) decision rules.

Even though the heavy advertisers in the top-left cell only account for 39.57% of the brands, they represent 96.15% of the total advertising over the 3-year estimation period. Of these 296 brands, only 140 would comply with the Steenkamp et al. (2005) decision rules. These 140 brands account for 63.76% of all advertising expenditures. The remaining 11 of the 151 brands which would comply with these rules would account for only 0.16%. Limiting ourselves to these 151 brands would hence result in a loss of information on more than 1/3 of all advertising expenditures by branded products, in which especially the focus on large brands appears to have strong consequences for the amount of advertising that is covered by the analyses. However, even though infrequent advertisers account for only a small part of total advertising expenditures, they still represent a large number of players, and hence in total as well a large number of advertising actions. By including them as well in our analyses, we can provide a better understanding of advertising in the market as a whole, thereby also providing evidence on how behavior may differ for smaller vs larger and more vs less frequently acting brands.

As a second main data source, we had access (through TNS) to consumer panel purchase data covering all purchases for over 17,000 families. These were used to calculate (i) the market shares of the different players, (ii) the category concentration and, (iii) the extent of category growth. Finally data on new product introductions (see e.g. Sorescu and Spanjol, 2008) were obtained through ProductScan©.

Measurement

We now turn to the measurement of the different constructs. In section 4, we already provided an in-depth discussion of the *Adstock* and *Ad-sensor* concepts. The brand-specific lambdas were obtained by a Bayesian regression estimation of a partial adjustment sales model (Hanssens et al., 2001 p. 147), thereby allowing for correlations between brands' sales within the same category. An overview of the procedure can be found in appendix D. To account for the uncertainty in the estimated lambdas, we use each of the 60,000 draws of the lambdas obtained after burn-in of 30,000 draws to calculate brand-specific Adstock and Ad-sensor series. These 60,000 series are subsequently used in the actual model estimation, with a burn-in of 30,000 and sample of 30,000 draws for inference.

Advertising frequency equals the percentage of time the brand was advertised during the 52-week initialization period. In the choice of the data range to determine this factor, the aim is to match as closely as possible the estimation sample. However, as we analyze advertising decisions, Advertising frequency could suffer from endogeneity problems when estimated on the 156-week estimation period. This made us opt to determine the factor based on the 52-week initialization period. These endogeneity problems, however, are not as severe for *Brand market share,* which is consequently defined as the average market share over the 156-week estimation period.

The first four weeks a new product is on the market, *New product introduction* will equal 1; the other weeks 0. Similarly, the last four weeks of the year, the *End of year budget depletion* dummy variable will equal 1; the other weeks 0. *Competitive adstock* is defined as the weighted average of the competitors' Adstock values. The weights are dynamic, and based on the market share in volume terms over the previous 26 weeks (see e.g. Nijs et al., 2001; 2007). *Relative performance evolution* is expressed by the first difference of the logarithm of the brand volume shares (see e.g. Deleersnyder et al., 2004), also defined over a moving window of the previous 26 weeks. *Category growth* is measured as the first difference of the log-transformed category volume sales (cfr. Franses and Koop, 1998). Finally, the Herfindahl index of volume shares over the previous 26 weeks period is used to quantify the *Category concentration*. All operationalizations are summarized in appendix E.

II.6. EMPIRICAL ANALYSIS

The coefficient estimates are shown in tables II.3 and II.4. They show the 95% posterior density intervals for the estimates, the latter printed in bold if zero is not included in the interval.

Adstock Management

Adstock. Table II.3 shows the expected positive effect of Adstock on the likelihood of advertising actions ($\overline{\zeta}_{1,1,0}$ = *0.241*). The conclusions of the stream of normative literature that advertising in most instances can best be scheduled in pulses or campaigns, appear to be adopted by the market. Brands show a clear state dependence, with periods of advertising during which the Adstock is rebuilt followed by periods during which it is allowed to deplete again. This state dependence, moreover, is also shown by the positive effect of Adstock on the magnitude of advertising actions ($\overline{\varpi}_{1,1,0}$ = *0.011*). More intense actions during the previous weeks of an advertising campaign, resulting in higher Adstock levels, will be followed by higher spending in subsequent actions, implying that brands either opt for consistently high or low intensity campaigns.

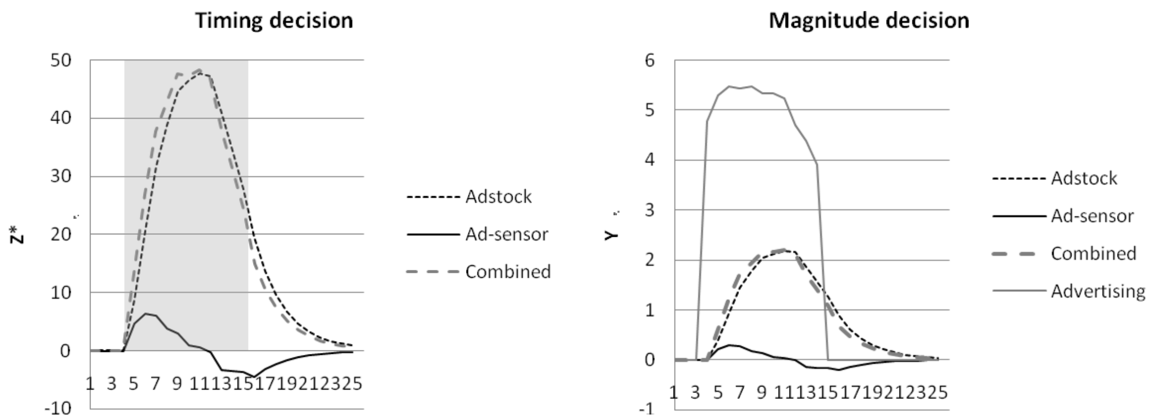
Table II.3. Adstock management: parameter estimates

	Timing				Magnitude			
		2.5th percentile	Median	97.5^{th} percentile		2.5^{th} percentile	Median	97.5^{th} percentile
Adstock	$\overline{\zeta}_{1,1,0}$	0.198	**0.241**	0.289	$\overline{\varpi}_{1,1,0}$	0.006	**0.011**	0.017
x Brand market share	$\overline{\zeta}_{1,1,1}$	*0.512*	***1.009***	*1.529*	$\overline{\varpi}_{1,1,1}$	*-0.028*	*0.004*	*0.035*
x Advertising frequency	$\overline{\zeta}_{1,1,2}$	*0.638*	***0.781***	*0.933*	$\overline{\varpi}_{1,1,2}$	*0.028*	***0.041***	*0.052*
Ad-sensor	$\overline{\zeta}_{1,2,0}$	0.107	**0.130**	0.150	$\overline{\varpi}_{1,2,0}$	0.066	**0245**	0.454
x Brand market share	$\overline{\zeta}_{1,2,1}$	*0.417*	***0.663***	*0.915*	$\overline{\varpi}_{1,2,1}$	*-0.002*	*0.019*	*0.041*
x Advertising frequency	$\overline{\zeta}_{1,2,2}$	*0.131*	***0.208***	*0.295*	$\overline{\varpi}_{1,2,2}$	*0.009*	***0.017***	*0.025*
Brand market share	$\overline{\zeta}_{1,0,1}$	-0.089	0.822	2.325	$\overline{\varpi}_{1,0,1}$	0.066	**0.245**	0.454
Advertising frequency	$\overline{\zeta}_{1,0,2}$	4.735	**5.192**	5.586	$\overline{\varpi}_{1,0,2}$	0.512	**0.592**	0.670

Ad-sensor shows a significant positive effect in the starting and stopping of advertising campaigns ($\overline{\zeta}_{1,2,0}$ = *0.130*). When the Ad-sensor values become too high, a brand will start advertising. The closer to the desired maximum goodwill level in the campaign, the more likely the brand will stop advertising. Once the target has been reached, negative values of the Ad-sensor will increase the pressure to stop advertising even further. Over time, however, the pressure to start a new campaign will start building again. Moreover, as long as one is still far away from the goal level of Adstock for that specific campaign, i.e. when the Ad-sensor has relatively higher levels, it will also remain a source of pressure to spend more in order to reach the desired level faster ($\overline{\omega}_{1,2,0}$ = *0.006*). Once the desired target has been reached, it gives clear indications to no longer spend large amounts in case the brand would still decide to advertise. This also captures quite well the phenomenon of make goods: the target level was reached, but still some smaller remaining advertising can still be found at the end of the campaign.

The effects of Adstock and Ad-sensor for our numerical example, as well as their combined effect, are represented in figure II.8. This is an illustration for an 'average' brand, with zero-effects of the mean-centered moderators. The first panel of figure II.8 shows the effects on the timing decision, in which the period during which advertising is taking place is indicated by the grey zone. The second panel subsequently shows the effects on the magnitude decision

Figure II.8. Effects of Adstock and Ad-sensor on timing and magnitude decision for our example



Moderating factors of Adstock and Ad-sensor

Brand market share. The larger brands in our set are likely to spend more on individual advertising actions ($\overline{\omega}_{1,0,1}$ = *0.245*). As marketing budgets are often set as a percentage of sales of previous periods (e.g. Allenby and Hanssens, 2005), more powerful brands will have larger budgets at their disposal, leading to more intense behavior. These brands, however, do not show differential baseline preferences in relation to their timing decisions.

Larger brands are better able to respond to their internal advertising pressure relative to smaller brands. Our results show that this is certainly the case in the timing decision ($\overline{\zeta}_{1,1,1}$ = *1.009*, $\overline{\zeta}_{1,2,1}$ = *0.663*). However, in the magnitude decision, no significant effects could be found.

Advertising frequency. Brands advertising more frequently in the past will continue to do so ($\overline{\zeta}_{1,0,2}$ = *5.192*). This is in line with previous research showing that current brand actions are often strongly influenced by previous behavior due to inertia effects (e.g. Frederickson and Iaquinto, 1989; Nijs et al., 2007). In addition, these brands will also spend more when advertising ($\overline{\omega}_{1,0,2}$ = *0.592*), confirming that basically two types of advertisers can be found: high-intensity (advertising often, spending more per decision) and low-intensity (advertising less often, spending less on single actions), as was already argued in the data section.

Our findings confirm the hypotheses that the effects of both Adstock and Ad-sensor are stronger for more experienced brands, and this for both the timing and magnitude decisions ($\overline{\zeta}_{1,1,2}$ = *0.781 and* $\overline{\omega}_{1,1,2}$ = *0.041, respectively;* $\overline{\zeta}_{1,2,2}$ = *0.663 and* $\overline{\omega}_{1,2,2}$ = *0.017, respectively*).

The resulting effects for both Adstock and Ad-sensor are depicted in figures II.9 and II.10. Figures are based on low (10) vs high (50) Adstock and low (-5) vs high (10) Ad-sensor values. The graphs in figure II.9 show the effect of Adstock and Ad-sensor in the Timing decision for low vs high values of Brand market share and Advertising frequency. The graphs in figure II.10 show the effects for the Magnitude decision.

Figure II.9. Effect of Adstock and Ad-sensor on timing decision as a function of Brand market share and Advertising frequency

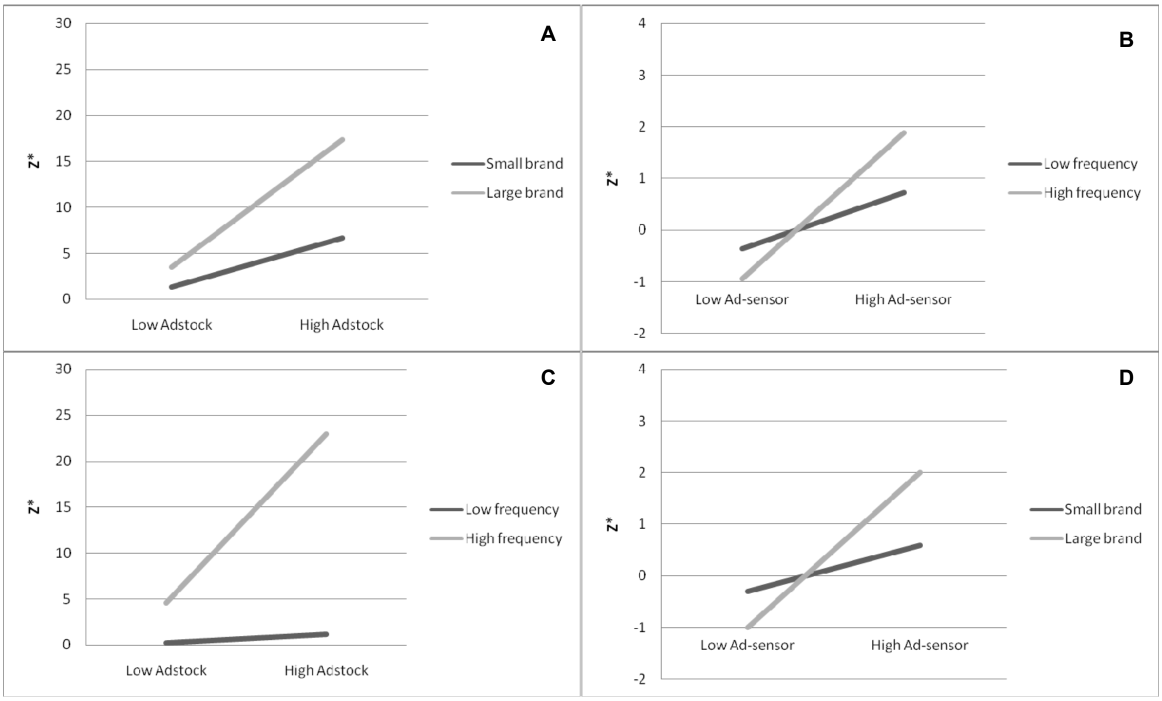
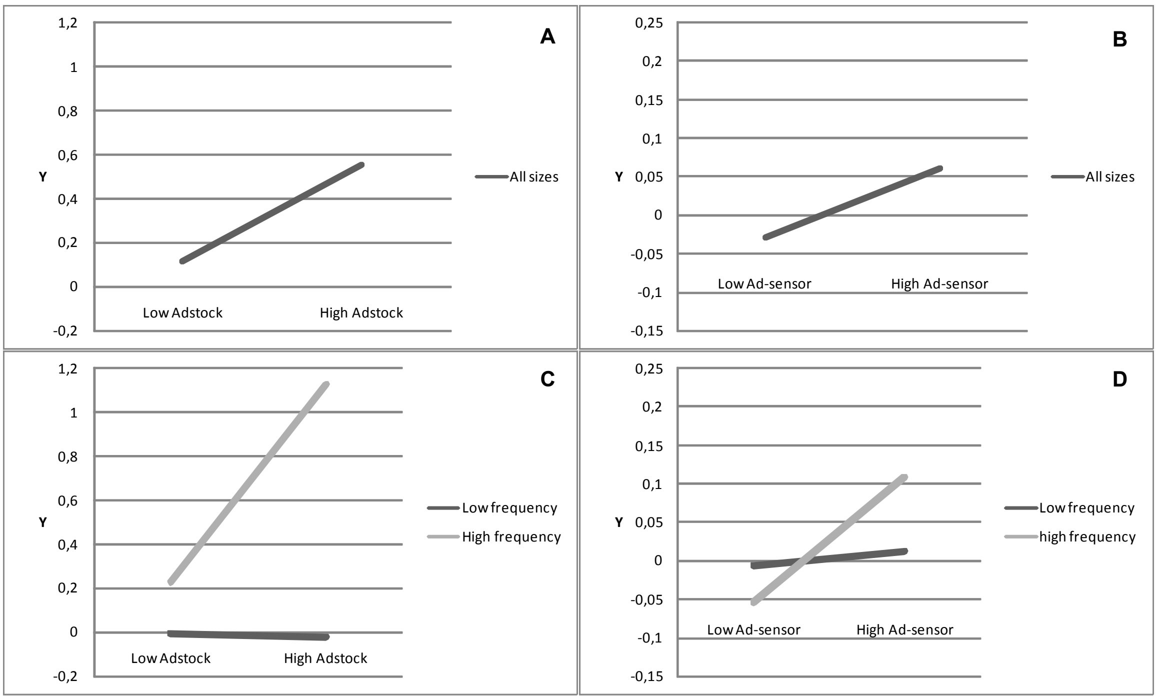


Figure II.10. Effect of Adstock and Ad-sensor on magnitude decision as a function of Brand market share and Advertising frequency



Moderating effects are reasonably strong for the Adstock effect. Larger and more experienced brands show much stronger campaigning behavior (panels II.9a and II.9c). They have more and better means and capabilities to pursue longer campaigns. More experienced brands will also be more likely adopters of consistently high or low advertising campaigns, as they as well show higher state dependence in their spending decision (panel II.10c). Similarly, larger and more experienced brands can better track their Ad-sensor, and will more strongly react to its evolution in their decision on whether or not to start/stop a campaign (panels II.9b and II.9d). In the beginning of a campaign, Ad-sensor is high. Combined with a strong response coefficient for more experienced brands, this will cause a faster and stronger build-up at the beginning. The combination of a strong response coefficient and negative Ad-sensor values after the target level was reached, in turn, will result in a strong tendency of more experienced brands to refrain from investing relatively large amounts after the target level was attained (panel II.10d).

Impact of baseline advertising preference drivers and covariates

Table II.4 reports the parameter estimates of time-invariant baseline advertising preference drivers and the set of time-varying covariates we included in our analysis. We do not discuss the effects of Brand market share and Advertising frequency as they were already reported above, but include them for reasons of completeness. For similar reasons, we also report the effects of the product class variables which were added to the model as control variables.

Competitive Adstock. Neither in timing nor size of their advertising actions, brands seem to be guided by their competitors. Although it has been shown that advertising clutter lowers advertising effectiveness (e.g. Villas-Boas, 1993; Danaher et al., 2008), brands do not refrain from spending when competitive advertising actions are likely, neither do they engage in a competitive escalation as was argued by Metwally (1978). Although perhaps surprising to some, this is in line with research by Steenkamp et al. (2005), who found little evidence of reactions with advertising to sudden competitive advertising shocks. Brands appear not to retaliate with a new own advertising action to those of competitors, nor will they spend more when advertising.

Table II.4. Baseline advertising drivers and covariates: parameter estimates

		Timing				Magnitude		
		2.5th percentile	Median	97.5th percentile		2.5th percentile	Median	97.5th percentile
Brand market share	$\bar{\zeta}_{1,0,1}$	-0.089	0.822	2.325	$\bar{\varpi}_{1,0,1}$	0.066	**0.245**	0.454
Advertising frequency	$\bar{\zeta}_{1,0,2}$	4.735	**5.192**	5.586	$\bar{\varpi}_{1,0,2}$	0.512	**0.592**	0.670
Food	$\bar{\zeta}_{1,0,3}$	-0.641	**-0.319**	-0.022	$\bar{\varpi}_{1,0,3}$	-0.073	-0.016	0.042
Drinks	$\bar{\zeta}_{1,0,4}$	-0.028	0.273	0.587	$\bar{\varpi}_{1,0,4}$	-0.069	-0.020	0.026
Cosmetics	$\bar{\zeta}_{1,0,5}$	-0.081	0.319	0.666	$\bar{\varpi}_{1,0,5}$	0.005	**0.062**	0.121
Competitive Adstock	$\bar{\zeta}_{1,3,0}$	-0.033	-0.011	0.016	$\bar{\varpi}_{1,3,0}$	-0.006	-0.002	0.002
Relative Performance Evolution	$\bar{\zeta}_{1,4,0}$	-0.152	-0.066	0.075	$\bar{\varpi}_{1,4,0}$	-0.050	-0.005	0.026
New Product Introduction	$\bar{\zeta}_{1,5,0}$	-0.138	0.412	0.807	$\bar{\varpi}_{1,5,0}$	-0.013	0.039	0.082
End of Year Remaining Budget	$\bar{\zeta}_{1,6,0}$	-0.324	**-0.252**	-0.177	$\bar{\varpi}_{1,6,0}$	-0.030	**-0.017**	-0.008
Category Growth	$\bar{\zeta}_{1,7,0}$	7.583	**8.310**	8.652	$\bar{\varpi}_{1,7,0}$	0.736	**0.908**	0.983
Market Concentration	$\bar{\zeta}_{1,8,0}$	-3.653	**-3.340**	-3.159	$\bar{\varpi}_{1,8,0}$	-0.148	-0.073	0.005

Relative performance evolution. Brands that perform well and gain market share have better means to compete. Larger marketing budgets become available (e.g. Allenby and Hanssens, 2005), enabling them to advertise more often and spend more. Conversely, the idea prevails that brands act in order to correct for a negative performance evolution relative to competitors (e.g. Metwally, 1978; Armstrong and Collopy, 1996). These theories are countered by our findings, as brands do not react with increased spending to make up for short term negative sales evolutions. Advertising budgets, on the other hand, are not adjusted immediately according to increased sales, leading to overall insignificance of short term performance evolution on advertising behavior. Advertising thus proves to be a strategic means of competition rather than a short term tactic means.

New product introduction. Advertising has been shown to be most effective for new products (Lodish et al., 1995) as it, e.g., increases trial probability of such products (Steenkamp and Gielens, 2003). New products still need to persuade customers into buying them. As advertising is an effective means to build awareness and convey product information, new products should be advertised more heavily (Tellis, 2004; Kotler and Armstrong, 2005). However, although our findings point in that direction, no such significant effects could be found on the actual advertising decisions.

End of year budget depletion. Advertising budgets are mostly set on a yearly basis, based on rules of thumb (e.g. percentage of sales of the previous year), formal advertising response modeling and management judgments (Farris and West, 2007). During the year, these budgets are used for advertising campaigns, driven by a wide set of factors (e.g. Montgomery et al., 2005). Thus, these financial resources become depleted. Our results indicate that managers tend to spend relatively more in the beginning of the year, making them advertise less often and spending less on single actions at the end ($\overline{\zeta}_{1,6,0} = -0.252$ *and* $\overline{\omega}_{1,6,0} = -0.017$), after accounting for Holiday season spending. Having money seemingly leads to spending it. In the beginning of the year, resources are still large, so one can more easily engage in more intense actions. As resources get depleted, one has to become more careful in when and what to spend, especially if one has spent relatively more in the beginning and hence has already used 'too much' of the resources.

Category growth. When category growth is higher, brands will be more inclined to advertise ($\overline{\zeta}_{1,7,0} = 8.310$), and their subsequent actions will as well be more intense ($\overline{\omega}_{1,7,0} = 0.908$). High growth categories are often younger product categories, requiring more advertising to inform and convince new customers (Narayanan et al., 2005). Consumers in more mature markets, with lower to zero growth, relay mostly on own experiences, and pay less attention to advertising (Chandy et al., 2001). Higher growth, in addition, can be considered an indicator of potential future profits, leading brands to defend their position even more fiercely (Gatignon et al., 1990).

Category concentration. Economic theory tells that more concentrated markets show higher profits as such oligopolistic markets are often characterized by barriers to entry (e.g. Bain, 1951; Modigliani, 1958; Karakaya and Stahl, 1989). Combined with the easy monitoring of competitors' actions in such markets, this may lead to collusive behavior and the use of non-price forms of competition such as advertising in order not to compete away these attractive margins (Ramaswamy et al., 1994; Lipczynski and Wilson, 2001). Our findings, however, indicate that brands appear to be less inclined to advertise in more concentrated categories ($\bar{\zeta}_{1,8,0} = -3.340$). This is in line with previous research by Steenkamp et al. (2005) showing less overall competitive interaction behavior in such categories. Brands thus advertise less often, although no effect on their actual spending when advertising could be found.

Validation

To find guidance on the relative performance of our model, we compare the proposed model (Model 0) to two other plausible specifications. In the first competing model (Model 1), we restrict all covariances between error terms to zero. Model 2 is specified with only the Adstock level but without the Ad-sensor, thus only accounting for the state dependence and not for the pressure to start or stop advertising.

To compare these models, we assess to what extent they are capable of predicting both timing and magnitude of advertising actions. We compare the models regarding their performance on four different prediction statistics. The first statistic we consider, is the Mean Squared Error, one of the most widely used loss functions in statistics. Theil U allows us to judge the performance of the models relative to a naïve no-change model. The closer the value to zero, the better the model performance over the naïve no-change model in which $y_{cbt} = y_{cbt-1}$. We implement the so-called U2 specification (Theil, 1966), which allows to make a distinction between models performing better or worse, as it allows values beyond 1. The hit rate provides evidence on the percentage correctly predicted Timing (0/1) decisions. Finally, we report the correlation between the predicted and observed advertising expenditures. Higher values for the latter two statistics prove better fit of the model. The best values on each summary statistic are underlined

The model performance statistics are considered both in- and out-of-sample. Indeed, as Van Heerde and Bijmolt (2005) argue, such time-based split provides us with a model robustness check as the estimation and validation samples may differ in a systematic way. Parameter estimates are based on a 130 week (2½ year) estimation period. The remaining 26 weeks (½ year) are used as a time hold-out sample. In the spirit of e.g. Brodie and de Kluyver (1987), we include *observed* Competitive Adstock, i.e. we assume that competitive actions are known. An overview of these statistics is given in table II.5.

In-sample performance

Our specification (Model 0) outperforms the alternative specifications on three diagnostics with regard to in-sample estimations. Although the hit rate (89%) is slightly lower than in model 1, our result is still impressive, especially when compared to the expected result for a random model. Given 24% of the observations showing advertising actions, a random model would show an overall hit rate of no more than 64% (Morrison, 1969). By means of such random model, we would a priori choose to classify α = 24% of the observations as actions. The observations, in turn, have an a priori probability of being an advertising action of p = 24%. The resulting hit rate would then equal $p*\alpha+(1-p)*(1-\alpha)=$ 0.24*0.24+0.76*0.76 = 0.64. In addition, when we decompose our hit rate into the percentage of correctly predicted actions and no-actions, we obtain results of 71% and 95% respectively, far beyond the expected values of 24% and 76%. Besides a good predictor of the timing decisions, our model as well proves high in-sample fit when correlating the predicted with the actually observed expenditures, with a correlation equal to 0.779.

Table II.5. Model comparison

Model	Description	In-Sample			
		MSE	Theil's U	Hit Rate	Correlation
Model 0	Proposed model	<u>0.078</u>	<u>0.552</u>	0.891	<u>0.779</u>
Model 1	No correlations	0.120	0.684	<u>0.893</u>	0.675
Model 2	No Ad-sensor	0.094	0.608	0.870	0.739

Model	Description	Out-of-Sample			
		MSE	Theil's U	Hit Rate	Correlation
Model 0	Proposed model	<u>0.141</u>	<u>0.749</u>	0.829	<u>0.588</u>
Model 1	No correlations	1.144	2.130	<u>0.839</u>	0.214
Model 2	No Ad-sensor	0.152	0.770	0.810	0.540

Out-of-sample performance

The second part of table II.5 summarizes the out-of-sample performance statistics of our validation models. Here as well, our focal model 0 outperforms the other models on 3 out of the 4 statistics. The hit rate (about 83%) and correlation (0.588) are still impressive. Decomposition of the hit rate shows correct predictions of action in 60% of the cases, and a correct prediction of non-actions in 90% of the cases. These are still far beyond the aforementioned expected values of 24% and 76% of a random model (Morrison, 1969). Overall, this provides evidence of the excellent predictive validity of our model specification.

Timing and Magnitude

In our study, we allowed for differential decisions processes in the timing and magnitude decisions. We already provided evidence of the good performance of our model in predicting the timing decisions by means of an impressive hit rate. In addition, we reported the overall correlation between observed and predicted advertising values. To more specifically assess the relative value of the magnitude part, we now restrict ourselves to those observations for which the outcome of the timing decisions was positive. Thus we obtain the following in-sample (out-of-sample) statistics: MSE = 0.199 (0.330); Theil U = 0.431 (0.548); correlation = 0.512 (0.407). These results indicate that the large share of correctly predicted zero advertising in the overall sample – and thus the good performance of the timing part – may inflate the overall correlation. Our model consequently performs better in predicting the timing of the advertising actions relative to predicting the actual amounts spent when advertising.

Based on these analyses, we can conclude that our model provides an encouraging mimicking of advertising decisions in the marketplace. Not accounting for the correlations between the error terms generally worsens the performance of our model. Finally, the inclusion of our Ad-sensor, capturing the process leading to the start and stop of an advertising campaign, clearly adds value compared to models including only the Adstock level.

II.7. DISCUSSION

Summary

Notwithstanding the fact that advertising is one of the most used marketing tools, little is known about what is driving the timing and magnitude of advertising actions. Building on normative theory, we developed a parsimonious model that captures this dual investment process. We explained advertising spending patterns as observed in the market, and investigated the impact of company, competitive, and category-related factors on these decisions. Analyses were based on a combination of (i) weekly advertising data from a wide variety of CPG brands from the UK, (ii) household panel purchase data, and (iii) data on new product introductions. We included both large and small brands, both frequent and infrequent advertisers in order to avoid data pruning biases, and to obtain a more complete overview of the market.

The empirical findings provide broad support for our conceptual framework. Adstock and Ad-sensor have a positive effect on both timing and magnitude decisions. Advertising spending patterns can hence be considered a result of the application of campaigning strategies, based on dynamic Adstock management systems. The extent to which such strategies are more or less the outcome of such systems, however, varies across brands as a function of their size and advertising frequency, a clear indication that inclusion of all types of brands in our dataset was warranted.

Discussion

In this study, we explained observed advertising spending patterns. Even strategies with same amounts of advertising in every single week, as were advocated by early normative studies (e.g. Zielske, 1959; Sasieni, 1971; 1989), are not observed in real world data. Pulsing strategies on the other hand, characterized by an alternation of periods with higher advertising and periods with lower to zero advertising (e.g. Mahajan and Muller, 1986) emerge as a dominant strategy. Differing from previous advertising research, we argued these advertising investments to be the outcome of a dual decision process, thereby distinguishing between two conceptually different but at the same time closely linked decisions: whether to advertise or not (timing), and conditional upon the choice to advertise, how much to spend (magnitude). As our results indicated, differentiating between these two decisions is warranted. They are partly driven by different factors, and common drivers have clearly different weights in both decisions. Accounting for differential processes thus allows us to obtain a much richer view as well as a more correct understanding of what is driving observed behavior.

Both decisions were subsequently embedded in an advertising goodwill stock management system. Advertising investments are scheduled in campaigns of several weeks, during which brands will build advertising goodwill among consumers. Carry-over effects of advertising allow for longer periods without advertising, during which the goodwill will gradually decay. As such, the created advertising goodwill is managed in a dynamic way. Similar to strategies in other inventory management, this process can be described as an (s,S) inventory management system, by means of which brands in a systematic way monitor and adjust their advertising goodwill stock. Brands will decide to launch a new advertising action as soon as this stock falls below a certain minimum desired level s, and stop advertising once the desired (higher) target level S was reached. The Ad-sensor concept we developed in this study captures this pressure, not only to launch and stop a new campaign, but also to spend more when still far away from the target level in order to reach it faster. As such, it provides evidence of the dynamics associated with advertising campaigns. The state dependencies of such campaigns, i.e. the fact that they last for several weeks and that brands prefer consistent spending strategies within each campaign, in turn, are well represented by the Adstock concept. Ad-sensor and Adstock thus each capture a distinct feature of campaigning behavior: the campaigning dynamics (Ad-sensor) and the campaigning state dependencies (Adstock). Inclusion of both concepts in our analyses thus provides us with a complete view of advertising campaigns. Limiting our analyses to only one concept would clearly lead to a loss of information and a less precise view. Together, Ad-sensor and Adstock allow us to explain observed advertising spending patterns as real-life applications of the normative literature, in which advertising and advertising goodwill management are embedded in dynamic (s,S) inventory systems.

However, the extent to which such systems affect the actual advertising decisions clearly differs among different types of brands. Larger brands, as well as more frequently advertising brands, show a greater reactance to changes in their advertising goodwill. The former have better means to do so, whereas the latter may have learned from previous experience, resulting in a closer advertising goodwill stock management. Both findings, taken together, provide clear evidence that limiting the analyses to only the frequently acting large brands would have biased our results. Our flexible model specification, in contrast to previous work, allowed us to cover nearly all players in the market, thus avoiding data pruning biases. Given the number of brands that otherwise would have been excluded from our analyses, this certainly gives extra weight to our empirical generalizations.

Although advertising is often argued to be driven by competitive reasoning and reaction, no such tendencies could be found. Not only did we not find any direct effects of competitive advertising in the advertising decision making process, indirect effects through the relative performance evolution of the brands did not show significant impact either. This may seem even more surprising, as annual advertising budgets are often determined on a percentage of sales basis (e.g. Allenby and Hanssens, 2005), and given the well-known argument that companies advertise in order to retain market shares (e.g. Metwally, 1978; Armstrong and Collopy, 1996). Advertising, characterized by small short run elasticities (e.g. Assmus et al., 1984; Sethuraman and Tellis, 1991), takes time to build an effect in the mindset of customers (e.g. Assael, 1998; Kardes, 2002). Price promotions, on the other hand, show much higher short run elasiticities (Neslin, 2002; Bijmolt et al., 2005), making it a more interesting instrument to make up for negative sales evolutions in the short run. This is also in line with the findings by Steenkamp et al. (2005) who show that, in contrast to price promotions, advertising will hardly be used as a means to react to competitors. Advertising thus appears not to be a tactic means to counter negative evolutions in the short run, but rather a strategic means which builds goodwill that lasts. Anecdotal evidence from practitioners adds to our findings, as several advertising agency account managers confirmed that brands, in general, focus on their own internal advertising utility calculi, and much less on what their competitors are doing in their actual advertising decisions.

Recent research has shown that new product introductions, combined with heavier advertising, can result in higher sales and increased shareholder value (see e.g. Pauwels et al., 2004; Srinivasan et al., 2009), combined with a rejuvenated brand (Slotegraaf and Pauwels, 2008). This may as well be a consequence of the fact that advertising is especially effective for those new products (e.g. Lodish et al., 1995; Steenkamp and Gielens, 2003). However, no significant link between such introductions and advertising decisions could be found, although there were some weak indications in that direction. Overall, adopted strategies appear to be continued in a similar fashion, without granting much extra support to new products relative to those that are already present in the portfolio. Brands which already have intense advertising strategies in place, are likely to continue these strategies for the new products as well, whereas those with lower intensity strategies may simply not have the means to increase their efforts.

Directions for future research

In this work, we investigated and explained advertising spending patterns as observed in the market. We did not aim at modeling the particular decision process of individual managers, but mimic the advertising decisions as observed in the market by means of a paramorphic model (e.g. Hoffman, 1960; Slovic and Lichtenstein, 1971; Steenkamp, 1989). Past research has proven that such models, although showing deviations when applied to specific individual reasoning processes, perform very well in capturing judgment and decision processes at a higher level (e.g. Einhorn et al., 1979). Thus we are able to capture the phenomenon that is taking place in the market, abstracting from short term individual deviations. However, this provides an avenue for future research focusing on how individual managers in practice decide on their advertising actions, and this by means of in-depth personal interactions with individual managers.

A second limitation of our work, is the fact that we limit ourselves to the dual decision of timing and magnitude, thereby aggregating over all media. Media choice as such is not investigated. This, however, would represent an interesting area for future research, as not all media show the same effectiveness for different product categories, and as synergy effects can be present in multimedia communications (see e.g. Naik and Raman, 2003). Moreover, media effectiveness is not static, but does evolve as well as a consequence of the appearance of new media. These phenomena can have far-reaching implications for the advertising decision process and render it even more complicated.

Brands often show highly volatile behavior in the goodwill levels at which they start and stop advertising. In our work, we therefore argued that the desired target advertising goodwill level S en allowed minimum level s are dynamic, i.e. that they can vary across campaigns. A closer investigation (i) of whether and to what extent these (s,S) choices are truly dynamic, and if so, (ii) of what is driving the volatility in these levels could consequently only add to our insights in the observed advertising spending patterns.

Computing limitations (with the present runtime of our model on a fast Dell Precision Workstation equaling 30 days) made us opt to include only time-invariant moderators in our model. However, the inclusion of time-varying moderators like price-promotions would enrich our analyses even further, and would also enable us to capture the interplay between Adstock and advertising management and other instruments of the marketing mix.

Finally, we showed that commonly applied data pruning rules may engender results which are only valid for that specific subsample of the market, raising questions to the validity of the corresponding conclusions for the market as a whole. New econometric techniques enable us to include all different types of players, even those that would have been excluded by these pruning rules. An investigation as to what extent findings of previous research are valid for the market as a whole can therefore be suggested.

III

ADVERTISING AND PRICE EFFECTIVENESS OVER THE BUSINESS CYCLE

Abstract

In this study, we conduct a systematic investigation of the evolution in the effectiveness of two important marketing mix instruments, advertising and price, over the business cycle. Analyses are based on 163 branded products in 37 mature CPG categories in the UK, and this for a period of 15 years. The data are a combination of (i) monthly national sales data, (ii) monthly advertising data, (iii) data on the general economic conditions, and (iv) consumer survey data. Consumers are shown to be more price sensitive during contractions. In addition, spending patterns will be less consistent, implying smaller brand loyalty. Advertising elasticities, however, do not seem to be affected by economic downturns. Product involvement was shown to be an influential moderator of the final effect of advertising, price and carry-over effects on sales. Finally, although short run effectiveness of price differs between expansions and contractions, the long run effectiveness of both advertising and price is not altered by differences in the general economic conditions.

III.1. INTRODUCTION

Firms are under ever increasing pressure to justify their marketing expenditures. Once considered mere costs, these expenditures are more and more treated as investments that should deliver shareholder value (e.g. Srivastava et al., 1998). Improvement of the performance and accountability of their organizations are consequently top concerns for senior marketing managers (CMO Council, 2009) since *"…companies are more interested than ever in understanding and measuring the returns being obtained from marketing investments…"* (Marketing Science Institute, 2008).

This evolution towards greater accountability is reinforced in times of economic contractions, as every dollar starts to matter more. Firms facing difficult times tighten their belts, and marketing budgets are among the first to be reconsidered (McKinsey, 2009). The recent economic downturn is no exception to this (The Financial Times, 2008). Late 2008, Toyota Motor USA, for example, announced a cut of 10% across all marketing budgets, while GM announced economizing up to $600 million on its advertising and promotion budget up to 2012. By January 2009, 71% of all marketing managers had reduced their advertising budgets, while 77% was planning to cut their media expenditures (Advertising Age, 2009). These examples illustrate that as the economy cools down, managers feel even more strongly the need to reconsider their marketing investments.

While there exists a considerable body of literature on marketing-mix effectiveness and elasticities in general (see e.g. Bijmolt et al., 2005; Hanssens, 2009 for recent overviews), previous research has not linked this to the business cycle. Does the effectiveness of marketing mix instruments vary across the business cycle, and if so, in what direction? What is the magnitude of the variation? Are there differences across marketing mix instruments, across brands and/or across categories? Although the subject of an intense debate, no systematic effort has been undertaken to provide answers to these questions. From a managerial point of view, insight into these questions helps companies in formulating their response to economic downturns. It provides them with a better understanding of the effectiveness of their investments. This enables them to better spread tighter budgets over the different marketing mix instruments, thereby answering the call for improved performance and accountability of the marketing organization. From an academic point of view, it is important to understand how the effectiveness of marketing mix instruments varies systematically over the business cycle. A good understanding of this evolution, is likely to add to our understanding of other observed phenomena as well. Private label success, for instance, has been shown to exhibit cyclical patterns, with systematic market share gains during downturns (Lamey et al., 2007). The purpose of the current study is to provide insights in these issues for two important marketing mix instruments, viz. Advertising and Price.

The remainder of this paper is structured as follows. We first review the previous literature (Section III.2), and describe how and why marketing effectiveness may vary across the business cycle (Section III.3). We subsequently explain the extraction of the business cycle components and the applied methodology in assessing the impact of the business cycle on advertising effectiveness (Section III.4). Next, we describe our data (Section III.5), and present our empirical findings (Section III.6) and managerial implications (Section III.7).

III.2. RELEVANT LITERATURE

The present study integrates three lines of research. Since the early days of marketing research, advertising and pricing effectiveness have been the subject of numerous studies, making them among the best covered issues in marketing science. More recently, a body of research focusing on marketing decisions over the business cycle has emerged.

Advertising effectiveness

Advertising effectiveness has been the focus of an impressive body of research (e.g. Lambin, 1975; Vakratsas and Ambler, 1999; for recent overviews, see Tellis and Ambler, 2007 or Hanssens, 2009). One of the first empirical generalizations in the domain was derived by Clarke (1976), who showed that 90% of the cumulative impact of advertising on sales occurred within months (and not years) of the advertisement. The advertising carry-over parameter λ of the Koyck model, which was driving this result, was reported to have a grand mean of 0.76 (Clarke, 1976). Assmuss et al. (1984) analyzed 128 studies assessing the impact of advertising on sales. They found the short-run advertising elasticity to have a grand mean of 0.221. In addition, they showed that not accounting for carry-over effects of advertising lead to considerable biases in the estimated short run effectiveness. A meta-analysis by Sethuraman and Tellis (1991) found the average short-run advertising elasticity to be only half of the previously mentioned value (0.109), according to the authors a possible consequence of people becoming more used to advertising.

Advertising has been shown to be relatively less effective for mature versus new products (Lodish et al., 1995). The authors also pointed out that spending more may not result in increased sales for well established and frequently advertising brands, indicating that they may already be advertising at saturation levels. Krugman (1965), in turn, showed advertising effectiveness to vary systematically with the level of involvement with the product.

Based on these insights, we will control for involvement when assessing the impact of economic fluctuations on advertising effectiveness. In addition, we will explicitly allow for carry-over effects.

Price effectiveness

Not surprisingly, also the quantification of the *price effectiveness* has received considerable research attention. In a first large-scale meta-analysis, Tellis (1988) covered over 367 elasticities related to 220 different brands or markets. The reported mean of -1.76 was considerably larger than the average advertising elasticity. A new meta-analysis by Bijmolt et al. (2005), based on 1851 elasticities, found the average price elasticity to be considerably higher than the one reported by Tellis (1988), i.e. -2.62. Higher inflation levels, in addition, were found to increase the price sensitivity, especially in the short run.

Similar to advertising elasticities, variation of price elasticities across brands and categories has been documented. Simon (1979) found a U-shaped relationship between the magnitude of price elasticities and the product life cycle, while Tellis (1988) reported stronger price sensitivities in the later stages of the product life cycle. Bijmolt et al. (2005), in turn, reported declining elasticies over the PLC. Finally, Sethuraman and Tellis (1991) examined the price/advertising elasticity ratio. They reported higher ratios for more mature products, which implies that lowering prices may be more profitable than increasing advertising for such categories.

Marketing decision making over the business cycle

Clearly, both marketing instruments have been studied extensively in prior research. However, we are not aware of any studies that have systematically linked these instruments' effectiveness to the state of the economy and its evolution through subsequent expansions and contractions. Though the linkage between such macro-economic fluctuations and marketing decision making, in contrast, has received increasing attention over the last few years, as reviewed in Table III.1.

A recurring finding in these studies is the fact that counter-cyclical advertising actions during economic downturns can create value for the company (Frankenberger & Graham, 2003; Srinivasan et al., 2005; Deleersnyder et al., 2009; Srinivasan and Lilien, 2009), which has been attributed indirectly to a presumed higher effectiveness during those periods. Other studies have focused on the level of marketing spending during contractions and expansions. Deleersnyder et al. (2009) showed that advertising expenditures are particularly sensitive to business cycle fluctuations, with strong increases during expansions and decreases during contractions. Such pro-cyclical advertising behavior, in combination with an increased price awareness during less favorable economic conditions (Estelami et al., 2001), has been linked with higher private label growth (Lamey et al., 2007; Deleersnyder et al., 2009). Private label share not only follows a counter-cyclical pattern, but also shows deepness and steepness asymmetries, with higher and faster growth during contractions and smaller and slower decline during expansions (Lamey et al., 2007). Pro-cyclical behavior, in turn, has also been observed in the context of new-product-introductions, where fewer new products tend to be introduced during economic downturns (e.g. Devinney, 1991; Axarloglou, 2003).

Table III.1. Previous studies on marketing decisions over the business cycle

Study	Key Metric	Main Findings
Devinney (1991)	New Product Introductions	Fewer new products are launched during economic downturns
Estelami et al. (2001)	Consumer Price Knowledge	Consumers are less price aware in economic upbeat times
Axarloglou (2003)	New Product Introductions	Fewer new products are launched during economic downturns
Frankenberger & Graham (2003)	Financial Performance	Increases in advertising expenditures (especially in combination with the introduction of new products) during crises create added value
Deleersnyder et al. (2004)	Durables' Sales	Durables show a pro-cyclical sales pattern Steepness asymmetry: decline is faster than recovery
Srinivasan et al. (2005)	Firm Performance	Pro-active marketing during contractions can be beneficial for brands with a strategic emphasis on marketing
Lamey et al. (2007)	Private Label Sales	Private label sales are higher during contractions Deepness and steepness asymmetries: decline is stronger and faster than recovery. Part of the private-label gain during contractions
Deleersnyder et al. (2009)	Advertising Spending	Advertising spending shows a pro-cyclical pattern
	Private Label Sales	More pro-cyclical advertising spending is associated with higher private label growth
	Firm Performance	Lower stock price performance for companies with pro-cyclical advertising patterns
Srinivasan and Lilien (2009)	Financial Performance	Increased R&D spending during contractions lower profits in B2B and B2C Increased advertising spending during contractions increase profits in B2B and B2C Effects last the year after the contractions

Moreover, pro-cyclical sales tendencies, whether or not due to pro-cyclical marketing expenditures, are a widespread phenomenon for branded products. They do not only exist in CPG markets, but are also reported in durables markets, which also tend to exhibit a faster decline than recovery (Deleersnyder et al., 2004).

This overview shows the increasing attention for the linkage between marketing decision making and the state of the economy. These studies, however, provide little to no evidence on the *effectiveness* of these decisions under different (expansion versus contraction) conditions. To address this issue, we derive the advertising and price elasticity of over 160 branded products in close to 40 CPG categories. This will allow us to not only derive empirical generalizations, but also to determine whether all brands/categories are equally affected by changing economic conditions.

The data span over 15 years of monthly data. The length of the time series allows us to cover multiple business cycles. As a result, inferences will not be driven by the idiosyncrasies of one specific expansion or contraction period (for a similar reasoning, see Deleersnyder et al., 2009, who also cover multiple business cycles). The disaggregate nature of the series, with their monthly observations, helps us to resolve two important issues. First,the periodicity of business cycles is 1.5 to 8 years (e.g. Burns and Mitchell, 1946; Christiano and Fitzgerald, 1998). When using annual data, the Nyquist frequency, i.e. the highest frequency about which direct information is available, corresponds to a component of 2 years (Granger and Hatanaka, 1964; Vilasuso, 1997). Higher frequency phenomena, i.e. short run fluctuations with a duration of less than 2 years, would hence not be removed from the data series. More disaggregated data, on the contrary, enable us to eliminate those higher frequencies as well. Second, from a market response perspective, annual data would introduce an aggregation bias in our analyses and inferences (see e.g. Hanssens et al., 2001). The usage of monthly data will mitigate this problem.

III.3. FRAMEWORK AND HYPOTHESES

The conceptual framework guiding our work is depicted in figure III.1. We argue sales to depend on two main types of factors: marketing-mix related factors, and macro-economic related factors. The final effects of these factors on sales are affected by the level of product-involvement the consumers show in the product category.

Cyclical sensitivity of sales

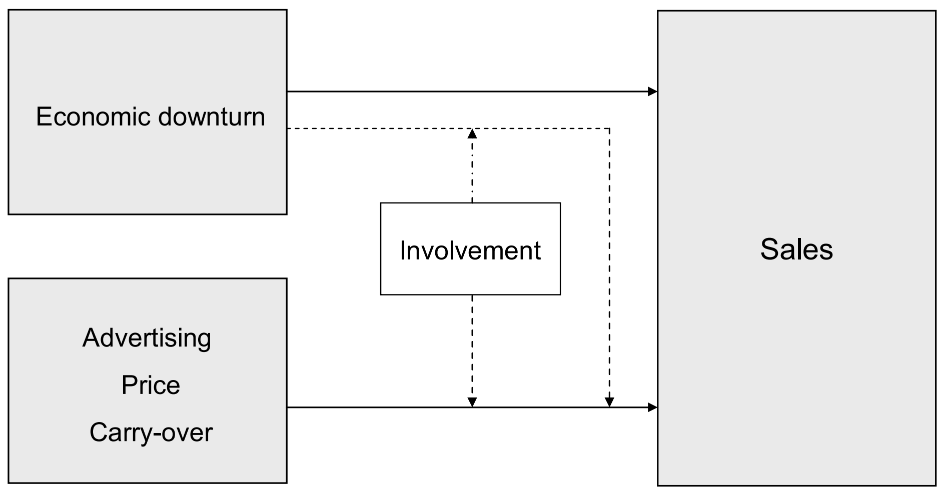
Economic downturns have a direct impact on both the ability and the willingness of consumers to spend their financial means. During economic sour times, consumers have fewer means at their disposal. In addition, consumers easily loose trust during contractions. As trust is a key factor in consumers' willingness to buy (e.g. Katona, 1975; Kamakura and Gessner, 1986; Allenby et al., 1996), they become hesitant to spend their money. Consumers have also been shown to easily switch to private-label offerings during economic downturns (Lamey et al., 2007), which further reduces the sales of branded products. As such, we expect a negative main effect of an economic contraction on brand sales.

Cyclical sensitivity of marketing effectiveness

Advertising. Although the overall elasticities have been found to be rather small (Asmuss et al., 1984; Sethuraman and Tellis, 1991), advertising still has a positive effect on sales. During economic downturns, this elasticity may increase. Overall reductions in advertising budgets (e.g. Deleersnyder et al., 2009) will give firms better chances in reaching the customer, as the firms face less competitive clutter (Danaher et al., 2008). At the same time, media rates are lower during contractions (e.g. Advertising Age, 2009). Further, increased advertising spending during economic tight times has been shown to positively influence firm profits (Srinivasan and Lilien, 2009), implying possibly higher advertising effectiveness.

These profits, on the other hand, may also be higher as a consequence of price increases during downturns (e.g. Backus and Kehoe, 1992; Rotemberg and Saloner, 1986; Rotemberg and Woodford, 1999; Deleersnyder et al., 2004), without advertising becoming more effective. By means of such price increases, firms try to make up for reduced sales quantities, thus preserving overall profits. In addition, during contractions, consumers focus more on the functional aspects of products instead of hedonic aspects as e.g. brand image, built by advertising (e.g. Ang et al., 2000). As a consequence, they may show lower reactivity to advertising, thus lowering the effectiveness of the advertising investments. The net effect of these processes on advertising elasticity is not clear a priori.

Figure III.1. Conceptual framework



Pricing. In their 2005 meta-analysis, Bijmolt et al show that the average price-elasticity equals -2.62. Common sense tells that during economic downturns, this elasticity will become even more negative (e.g. Block, 1977). Consumers' disposable income is usually lower in such periods, creating a higher level of price awareness and fostering a search for lower prices (Wakefield and Inman, 1993; Estelami et al., 2001). They express stronger appreciation for price cuts (Quelch, 2008), and are shown to switch to lower priced private label offerings (e.g. Quelch and Harding, 1996; Ang et al., 2000; Lamey et al., 2007). We therefore expect an increase in the magnitude of price elasticities during economic downturns

Carry-over. Besides the short run effectiveness of advertising and pricing, as captured by the previous variables, we are also interested in their long-run performance. The long run performance may not only change as a consequence of changing short-run elasticities, but also because of different carry-over effects across the business cycle, as brand loyalty is likely to be lower during contractions. First, when the economy turns sour, consumers experience a larger pressure on their disposable income. As a consequence, they show stronger switching behavior, and less brand loyalty (Chance and French, 1972). At each decision, consumers will engage in increased information gathering, thereby evaluating several alternative options to get the maximum out of their smaller budgets, (e.g. Block, 1977; Wakefield and Inman, 1993). Second, lower brand loyalty will translate into lower carry-over effects as brand loyalty implies a consistent purchase of the brand over time (Keller, 1993; Assael, 1998). Stronger switching behavior implies less consistent purchase patterns, and hence reduced carry-over. We consequently expect carry-over effects to be smaller during economic sour times.

The moderating role of involvement

Involvement is typically defined as the subjective perception of the personal relevance of an object, activity or situation (Van Trijp et al., 1996). Involvement will be higher with products that show considerable performance risk and symbolic value (Laurent and Kapferer, 1985). In high involvement product categories, consumers engage in more profound information gathering and decision making processes (Bloch et al., 1986; Assael, 1998). Advertising messages, for example, will be more actively processed (e.g. Petty et al., 1983). At the same time, decisions will not be based on just one or two factors, but will be multi-dimensional, with consumers evaluating a larger set of criteria (Park and Mittal, 1985). As a consequence, the relative weight of each criterion will be smaller, and effects on the final sales decision will be smoothed by effects of other factors. Lower involvement categories, on the other hand, do not require such in-depth processes as e.g. the associated risk will be lower (Hoyer, 1984; Hawkins and Hoch, 1992). In such categories, people will rely more on heuristics in order to reduce their cognitive effort (Tversky and Kahneman, 1974), thereby basing their decisions on very little information. Among the most used heuristics are e.g price, brand awareness, advertising and previous purchases (Desphandé, 1982; Hoyer, 1984; Warrington and Shim, 2000). These heuristics tend to retain a dominant effect, even after multiple sampling opportunities of other brands (e.g. Hoyer and Brown, 1990). Given the smoothing effect in the more elaborate higher involvement product decisions relative to the amplification effect of the use of simple heuristics in lower involvement product decisions, we expect the effect of external cues like marketing mix instruments and macro-economic evolutions to be mitigated by the level of product involvement. This, in turn, results in lower advertising and price elasticities for higher involvement products. This effect will be reinforced during contractions, with the impact of contractions on the advertising and price elasticities being smaller for higher involvement products.

Brand loyalty, the consistent purchase of the same brand over time (Keller, 1993; Assael, 1998), can result from two clearly distinct processes. Brand loyalty has been argued to be one of the choice heuristics which are used to reduce cognitive effort and simplify decision making for low involvement products (e.g. Warrington and Shim, 2000). In such cases, brand loyalty is nothing more than habitual buying behavior (e.g. Jeuland, 1979). Loyalty, on the other hand, can also be the outcome of in-depth information gathering processes in high involvement categories. Consumers have evaluated several different options in an elaborate process, and have concluded a certain brand to fit their requirements best (e.g. Newman and Staelin, 1972). Learning effects, in turn, will play an important role in subsequent decisions (Newman and Staelin, 1972; Punj and Staelin, 1983). Hence, if higher involvement increases loyalty, carry-over is expected to be higher for higher involvement categories. Conversely, if higher involvement attenuates consumer inertia, carry-over will be lower for higher involvement categories. The final effect is not clear a priori.

III.4. METHODOLOGY

In order to provide an answer to the issues raised in previous sections, we propose a methodology which consists of three steps. First, we extract the cyclical component in the macro-economic indicator series using a business cycle filter, and determine contraction and expansion periods. Next, we formulate a model which quantifies the advertising and pricing elasticities both during contractions and expansions. Finally, we explain cross-category variation in the cyclical sensitivity of these elasticities.

Extracting the cyclical component

To assess the impact of business cycles on marketing mix effectiveness, we first have to extract the cyclical component from the GDP series, as the latter is a result of slowly evolving secular trends, a cyclical component and rapidly varying seasonal and irregular components (Baxter and King, 1999). In order to do so, we adopt the widely used **B**axter-**K**ing (1999) band-pass filter (e.g. Stock and Watson, 1999; Deleersnyder et al., 2004). This filter decomposes the GDP series in a gradually evolving long run trend component and cyclical fluctuations around it, the focus of our interest. The BK band-pass filter tries to isolate cycles with period lengths between 6 and 32 quarters, which corresponds to the typical length of business cycles (e.g. Burns and Mitchell, 1946; Christiano and Fitzgerald, 1998). The filter itself is a symmetric moving average filter:

$$\text{(III.1)} \quad GDP_t^C = \sum_{j=-K}^{K} a_j L^j GDP_t$$

where GDP_t^C is the filtered series from the original time series GDP_t, with a_j the weights corresponding to the different leads and lags. These weights are given in appendix F. K, the number of included leads and lags, is to be set equal to 12 for quarterly data (Baxter and King, 1999). The resulting filtered series, is the business cycle component series we are interested in. Although our study is based on monthly data, the least aggregated GDP series available, is on a quarterly level. We therefore analyze the GDP series at the quarterly level, and subsequently translate our findings to the monthly level.

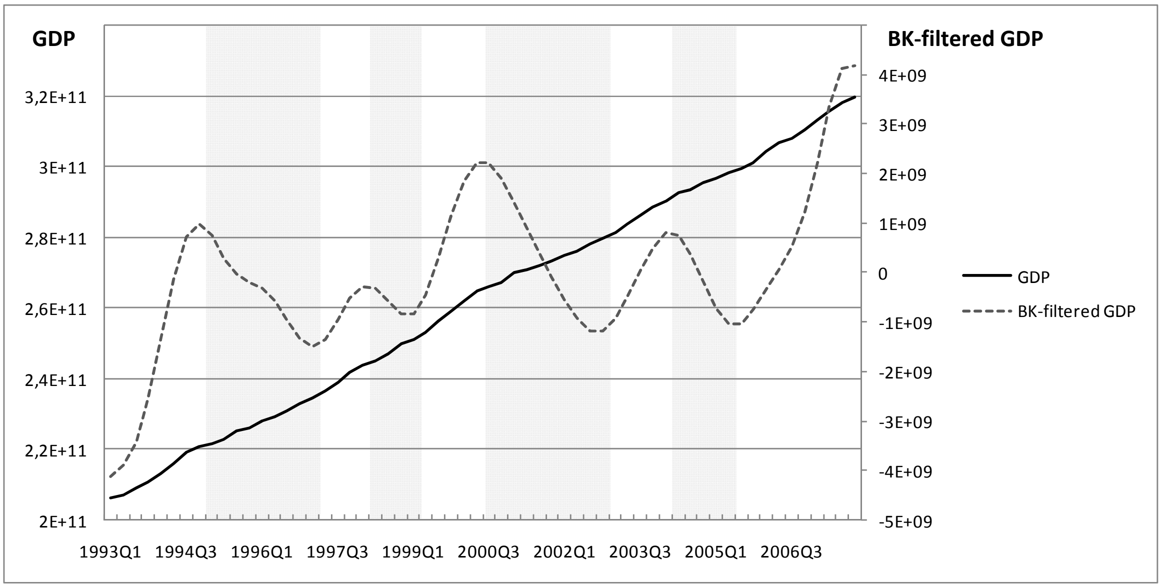
In the marketing literature on turbulent times, several studies (e.g. Lamey et al., 2007; Deleersnyder et al., 2009) adopted the **H**odrick-**P**rescott filter. Differing from our study, these were based on annual data. Baxter and King (1999) show that their BK band-pass filter is to be preferred for quarterly data. The most compelling reason is the fact that the BK filter also removes the higher frequency irregular variation in the series, something which is not accounted for by the HP filter. The latter can therefore be regarded as the high-pass part of the BK band-pass filter. Whereas such irregular short run variation is a less prominent issue in annual data, its removal is an important feature for quarterly data.

After the extraction of the cyclical component, we determine the contraction and expansion periods. Periods during which a decline in the cyclical component is observed, are categorized as contractions. Periods with an increase, in turn, are categorized as expansions. We include this dichotomy in our analyses by means of a 1/0 dummy variable (see Lamey et al., 2007 for a similar practice):

(III.2) $If\ GDP_t^C - GDP_{t-1}^C < 0\ then\ Contraction_t = 1;\ else = 0$

All months within a quarter which is marked as a contraction will show a value of 1 for the Contraction dummy variable. The original GDP series, the BK-filtered cyclical component and the associated contraction and expansion periods are depicted in figure III.2. The black line depicts the original GDP series, with values on the left axis. The dotted grey line gives the cyclical component, with values on the right axis. Finally, grey zones represent contractions, white zones expansions.

Figure III.2. GDP, BK-filtered GDP cyclical component and contraction and expansion periods



Assessing the impact of the business cycle on advertising and pricing effectiveness

When assessing the impact of the business cycle on advertising and pricing effectiveness, we face the following model requirements. First, we want to make abstraction of levels of expenditures, enabling us to draw conclusions across different types of brands and categories. Second, we allow the response parameters to vary across brands. Third, the performance of brands may be interrelated within a category, and hence we need to specify a full error covariance structure for each category. Finally, we need to accommodate the effects of moderating variables, preferably in a simultaneous estimation step for maximal statistical efficiency.

In line with previous research (e.g. Naik and Raman, 1998; Hanssens et al., 2001) we start from the following partial adjustment sales model:

$$\text{(III.3)}\quad \begin{aligned}\ln Sal_t^{cb} &= \beta_0^{cb} + \beta_1^{cb} Contraction_t + \beta_2^{cb} \ln Adv_t^{cb} + \beta_3^{cb} \ln Price_t^{cb} + \beta_4^{cb} Trend_t \\ &\quad + \lambda^{cb} \ln Sal_{t-1}^{cb} + \varepsilon_t^{cb}\end{aligned}$$

in which $\ln Sal_t^{cb}$ is the natural logarithm of the volume sales of brand b (b=1...B_c) in category c (c= 1…C) in month t (t=1…T). $Contraction_t$ is a dummy variable equaling 1 when the economy is in a contraction; 0 otherwise. $\ln Adv_t^{cb}$ is the natural logarithm of the advertising expenditures of brand b, whereas $\ln Price_t^{cb}$ is the natural logarithm of the price of that brand at time t. Finally, we account for the effect of possible other, trending, factors by including a deterministic trend $Trend_t$ (see e.g. Dekimpe and Hanssens 1995 for a similar practice) and allow for carry-over effects by including the lagged dependent variable as explanation variable. Since we specify the variables in natural logarithms, we can make abstraction of the actual level of the investments in our interpretations, as the parameter estimates represent the respective elasticities.

Differing from the first study in this dissertation, we do not include Adstock in our model. As argued in Leeflang et al. (2009), demand is essentially a *flow* variable. Period-to-period variations of such flow variables are mostly due to period-to-period variation in other *flow* variables like e.g. advertising and price. *Stock* variables like e.g. advertising goodwill stock and customer equity will rather affect baseline performance instead of leading to short-run variation. Hence, although Adstock was shown to play a crucial role in advertising decisions, the effect of such stock levels on short-run sales variations is likely to be limited. We therefore opted to include only the flow variable (Advertising) in our model, and not the stock variable (Adstock).

To account for the cyclical sensitivity of the marketing mix variables' effectiveness, we next introduce two interaction effects: $Contraction_t * \ln Adv_t^{cb}$ and $Contraction_t * \ln Price_t^{cb}$. We also investigate to what extent the long run effectiveness of these instruments may vary across expansions and contractions by including $Contraction_t * \ln Sal_{t-1}^{cb}$. Finally, by means of the $Trend_t$ we control for gradually changing factors which are not included in our model. As some of these factors may evolve differently because of changing overall economic conditions, we also add $Contraction_t * Trend_t$ to our model:

$$
\begin{aligned}
\text{(III.4)} \quad \ln Sal_t^{cb} = {} & \beta_0^{cb} + \beta_1^{cb} Contraction_t + \beta_2^{cb} \ln Adv_t^{cb} + \beta_3^{cb} \ln Price_t^{cb} + \beta_4^{cb} Trend_t \\
& + \beta_5^{cb} Contraction_t * \ln Adv_t^{cb} + \beta_6^{cb} Contraction_t * \ln Price_t^{cb} \\
& + \beta_7^{cb} Contraction_t * Trend_t \\
& + \lambda_1^{cb} \ln Sal_{t-1}^{cb} + \lambda_2^{cb} Contraction_t * \ln Sal_{t-1}^{cb} + \varepsilon_t^{cb}
\end{aligned}
$$

As sales evolutions of brands within a category may be correlated, we assume that the error vectors $\boldsymbol{\varepsilon}_t^c = (\varepsilon_t^{c1}, \ldots, \varepsilon_t^{cB_c})'$ of each category follow a multivariate normal distribution, with a full variance-covariance matrix per category: $\boldsymbol{\varepsilon}_t^c \sim MVN(0, \boldsymbol{\Sigma}_c)$. Sales of brands in different categories, on the other hand, are assumed not to be correlated.

Explaining cross-category differences

In a final step, we relate the marketing effectiveness parameters β_i^{cb} and λ_i^{cb} to product involvement:

(III.5) $\beta_i^{cb} = \overline{\beta}_{i,0} + \nu_{\beta_i}^{cb}$, for $i \in [0,1,4,7]$

(III.6) $\beta_i^{cb} = \overline{\beta}_{i,0} + \overline{\beta}_{i,1} Involvement^c + \nu_{\beta_i}^{cb}$, for $i \in [2,3,5,6]$

(III.7) $\lambda_i^{cb} = \overline{\lambda}_{i,0} + \overline{\lambda}_{i,1} Involvement^c + \nu_{\lambda_i}^{cb}$, for $i \in [1,2]$

Involvement is defined in the spirit of Laurent and Kapferer (1985) by also including aspects of Symbolic value and Perceived risk with buying the product. It is measured by multiple items, each scored on a five point Likert scale. Scores on the different items are averaged, resulting in one overall Involvement score. We subsequently mean-center the Involvement variable over the different categories, which allows us to formulate conclusions relative to the average category. The resulting series has a high of 0.358 and a low of -0.355, with a standard deviation of

0.175. As such, the variation in the series appears sufficiently high to possibly engender substantial effects in our analyses.

Unobserved drivers of model parameters may cause the error terms in (III.5), (III.6) and (III.7) to be correlated as well, so we assume that they follow a multivariate normal distribution, with a full variance-covariance matrix per brand: $(\mathbf{v}_{\beta}^{cb}{}', \mathbf{v}_{\lambda}^{cb}{}')' \sim MVN(0, \mathbf{\Omega})$.

We estimate model (III.4)-(III.7) with Bayesian techniques, i.e., Gibbs sampling. The benefit of this approach over classical approaches is that, at the same time, (i) it can more easily account for brand heterogeneity, as well as (ii) intra-category correlations (e.g. Rossi et al., 2005) and (iii) it estimates the moderator effects simultaneously with the other parameters rather than in a two-step approach. An overview of this procedure is given in appendix G.

Assessing long run performance

Based on our estimations, we analyze the long run effects of both advertising and price, and how they may vary across the business cycle. Derived from our partial adjustment sales model specified in (III.4), we can define the long run effects as (e.g. Hanssens et al., 2001):

(III.8) $\beta_{adv,LR}^{cb} = \dfrac{\beta_2^{cb}}{1-\lambda_1^{cb}}$ and $\beta_{price,LR}^{cb} = \dfrac{\beta_3^{cb}}{1-\lambda_1^{cb}}$ during expansions

and

(III.9) $\beta_{adv,LR}^{cb*} = \dfrac{\beta_2^{cb}+\beta_5^{cb}}{1-(\lambda_1^{cb}+\lambda_2^{cb})}$ and $\beta_{price,LR}^{cb*} = \dfrac{\beta_3^{cb}+\beta_6^{cb}}{1-(\lambda_1^{cb}+\lambda_2^{cb})}$ during contractions.

Significantly different short run and carry over effects during contractions versus expansions do not immediately imply significantly different long run effects. Both short run effectiveness and carry-over are estimated values, each with a confidence interval, possibly with opposing effects on the ratio. Their combined effect will hence depend on the relative sizes of these intervals and on the correlations. In our Bayesian estimation procedure, we therefore also draw both long run advertising and price effectiveness, as well as the change in both due to economic downturns. This allows us to calculate in a direct way confidence intervals for these long run effects, as well as for their differences between expansions and contractions.

III.5. DATA DESCRIPTION

Monthly volume sales data for 37 mature CPG categories in the United Kingdom (1993-2007) were provided by TNS UK. In each category, we selected the top 5 branded products which were present in the market for at least 95% of the time. Thus, our time series for the individual brands are sufficiently long to cover four business cycles (e.g. Deleersnyder et al., 2004). In total, we were able to include 163 brands in 37 markets in our sample. An overview of the included categories is given in table III.2.

Table III.2. Overview of included product categories

Product Class	Number of Categories	Examples
Food	15	Artificial sweeteners, Breakfast cereals, Butter, Tinned fruits,
Drinks	7	Fruit juices and drinks, Mineral water, Softdrinks, Tea
Toiletries	8	Bath additives, Dentifrice, Deodorants, Shampoo
Household Products	7	Household cleaner, Machine wash products, Toilet Tissues, Washing up products,

Table III.3 provides a set of summary statistics on the relative sizes of the brands, the evolution of their market share over the 15-year period, as well as the combined market share within the category of the included brands. Although we consistently focus on the five largest brands within each category, strong variability can be found both in the average brand market share over this period and in the market share evolution. The included brands, moreover, account for substantially different combined shares.

Table III.3. Market share statistics

	Mean	Spread
Average brand market share 1993-2007	0.107	0.005 – 0.699
Average brand market share evolution 1993-2007 (over the 15 years)	-0.001	-0.236 – 0.479
Average cumulative market share per category 1993-2007	0.471	0.101 – 0.911

The necessary price information on these brands was also obtained from TNS UK. These monthly sales and price data are subsequently combined with advertising data that were purchased from NielsenMedia UK. These data cover all advertising expenditures by the individual brands we consider, aggregated over Television, Print media, Outdoor, Cinema, Radio en Direct mail.

We use data on real GDP as a proxy for the general economic activity. The cyclical component of the GDP has proven to be a good indicator of the overall economic cycle, as it integrates business cycles fluctuations across many sectors (Stock and Watson, 1999). GDP data, expressed in constant prices, were obtained from the OECD. All marketing mix series are inflation-adjusted by means of the Consumer Price Index, which was also obtained from the OECD.

Finally, information on Involvement was obtained through a large-scale consumer survey (see e.g. Steenkamp et al., 2008 for an in-depth discussion). As mentioned in the section III.4, Involvement was defined in the spirit of Laurent and Kapferer (1985), by including references to perceived risk and social symbolism of the category.

Companies have been shown to adjust their marketing investments in reaction to business cycle changes (e.g. Deleersnyder et al., 2009). To obtain insights in the extent to which the brands in our sample adjust their advertising and prices in a reaction to economic contractions, we extract the cyclical components of their advertising and price series by applying the Baxter-King band-pass filter. These cyclical components are subsequently regressed on the contraction dummies. The business-cycle filter, however, may induce serial correlation (Engle, 1974). We therefore allow for an autoregressive error term when needed, based on the BIC (for similar practice see e.g. Lamey et al., 2007; Deleersnyder et al., 2009). The results are shown in table III.4.

Table III.4. Impact of contractions on marketing mix decisions

	Increase*	Decrease*	No Change
Advertising	19	28	116
Price	25	14	124

*Significant changes at the 0.10 level. two-sided test.

Changes in marketing investments appear rather limited for the brands in our sample. Among those brands that do change their investments, we observe large variation in the decisions. Nevertheles, there are some indications of the earlier reported tendencies to decrease advertising budgets (Deleersnyder et al., 2009) and increase prices (e.g. Backus and Kehoe, 1992; Rotemberg and Saloner, 1986; Rotemberg and Woodford, 1999; Deleersnyder et al., 2004). Of the 74 brands that thus significantly change their investments in at least one of the marketing mix instruments, only 12 modify their expenditures on both instruments. To test for overall significance of the changes, we applied the method of added Z's (Rosenthal, 1991). These tests showed that prices are not significantly increased ($p = 0.14$, one-sided), whereas there are indications that advertising expenditures are reduced ($p < 0.10$, one-sided).

III.6. EMPIRICAL ANALYSIS

The coefficient estimates are presented in table III.5. They show the 95% posterior density intervals for the estimates. These are printed in bold if zero is not included in the interval.

Cyclical sensitivity of sales

Economic downturns as such do not seem to impact sales of the included brands. This may be a consequence of the fact that most of these CPG categories can be considered necessities. Purchases of such products are not likely to, or cannot, be postponed until the economic conditions improve.

Table III.5. Parameter estimates

		Hypothesis	2.5th percentile	Median	97.5th percentile
Intercept	$\overline{\beta}_{0,0}$		-0.010	0.037	0.089
Contraction	$\overline{\beta}_{1,0}$	-	-0.019	0.001	0.026
Advertising	$\overline{\beta}_{2,0}$	+	0.002	**0.003**	0.005
x Involvement	$\overline{\beta}_{2,1}$	-	-0.015	**-0.008**	-0.000
Advertising*Contraction	$\overline{\beta}_{5,0}$	?	-0.001	0.000	0.001
x Involvement	$\overline{\beta}_{5,1}$	?	-0.008	-0.000	0.007
Price	$\overline{\beta}_{3,0}$	-	-1.207	**-1.075**	-0.927
x Involvement	$\overline{\beta}_{3,1}$	+	-0.795	0.004	0.872
Price*Contraction	$\overline{\beta}_{6,0}$	-	-0.242	**-0.148**	-0.060
x Involvement	$\overline{\beta}_{6,1}$	+	0.173	**0.590**	0.951
Carry-over	$\overline{\lambda}_{1,0}$	+	0.504	**0.535**	0.564
x Involvement	$\overline{\lambda}_{1,1}$	-	-0.379	**-0.203**	-0.035
Carry-over*Contraction	$\overline{\lambda}_{2,0}$	-	-0.074	**-0.053**	-0.032
x Involvement	$\overline{\lambda}_{2,1}$	+	-0.043	0.042	0.133
Trend	$\overline{\beta}_{4,0}$	?	-0.002	**-0.001**	-0.000
Trend*Contraction	$\overline{\beta}_{7,0}$	?	-0.000	0.000	0.001

Short run marketing effectiveness

Advertising. Consistent with Lodish et al. (1995) and Ataman et al. (2009), advertising elasticities are found to be particularly small for these types of mature consumer goods ($\overline{\beta}_{2,0}$ = *0.003*). As we hypothesized, higher involvement products show significantly smaller advertising elasticities ($\overline{\beta}_{2,1}$ = *-0.008*). Although advertising will be processed more thoroughly, the more elaborated decisions processes for higher involvement products lower the relative weight and hence the effect on the final outcome.

Price. As could be expected from previous literature (e.g. Bijmolt et al., 2005; Ataman et al., 2009), price elasticities are found to be much larger compared to advertising elasticities ($\overline{\beta}_{3,0}$ = *-1.075*). Contrary to our predictions, higher involvement product categories do not show smaller price elasticities.

Cyclical sensitivity of marketing effectiveness

Advertising. Business cycles do not seem to affect the short run effectiveness of advertising. Notwithstanding arguments supporting both an increase and a decrease of advertising effectiveness during economic contractions, no significant effects could be found.

Price. As we expected, price sensitivity increases during contractions ($\overline{\beta}_{6,0}$ = -*0.148*). This effect, however, will be mitigated when the involvement with the product category is higher ($\overline{\beta}_{6,1}$ = *0.590*). Price sensitivity does increase, but the effects will be stronger in those categories were decisions are usually based on simple heuristics like e.g. price. More involvement and hence more in-depth decision making will smooth the effect of price on actual sales.

Impact of Involvement

One of the central questions marketing managers have to decide on, is how to allocate their budgets over price reductions (by lowering the margins) and advertising actions. To provide answers to this question, we base ourselves on the framework developed by Dorfman and Steiner (1954). In their work, the authors argue that marketing budgets should be allocated relative to the ratios of the respective elasticities. More effective instruments, i.e. those showing higher elasticities, thus receive larger parts of the overall marketing budget. As Sethuraman and Tellis (1991), we therefore report the price/advertising elasticity ratios in expansion and contractions for products with different levels of Involvement. High and Low Involvement are defined as one standard deviation above and below the Average level, Very High and Very Low as two standard deviations above and below the Average level. The results are summarized in table III.6. The changes in the ratios provide us with an indication how relative allocation should be altered to improve short run performance.

Table III.6. Price-Advertising elasticity ratios

	Expansion	Contraction	% Change
Very Low Involvement	185.491	246.601	+33%
Low Involvement	244.444	301.539	+23%
Average Involvement	358.333	407.667	+14%
High Involvement	670.919	698.953	+4%
Very High Involvement	5255.182	4970.846	-5%

Overall, price/advertising ratios are remarkably high. However, the product categories under investigation are all well established mature CPG categories. For such products, advertising has been proven to be much less effective relative to newer products, whereas price does play a more important role in purchase decision making, leading to higher ratios relative to newer products (Sethuraman and Tellis, 1991). The ratios indicate that, for such mature products, firms can gain more by reducing their prices compared to investing in advertising campaigns. The extreme values for the Very High Involvement categories are a consequence of advertising showing very limited final effects on sales for such products (cfr. Ataman et al., 2009).

In general, firms are encouraged to increase their price efforts relative to advertising in the short run. For products showing Average Involvement, the short run price/advertising elasticity ratio increases with 14% during contractions. This is a consequence of the increased price sensitivity during contractions, with advertising sensitivity remaining stable over the business cycle. Sales gains are hence better achieved by price reductions than by advertising increases.

For lower Involvement categories, the change in recommended relative budget allocation will be even stronger. Although advertising is more effective for these products, resulting in lower overall ratios, price sensitivity will increase much stronger during contractions. As consumers feel the pressure on their reduced budgets, the price heuristic will become much more prominent in their decisions for low-involvement products. A clear shift in marketing budgets from advertising to price reductions is therefore warranted.

However, such shifts from advertising to price efforts are not recommended for all product types. For Very High Involvement product categories, the ratio shows an opposite evolution, with a relative change of the ratio with -5% towards advertising budgets. This change is not so much a consequence of changes in advertising effectiveness. Advertising elasticities are extremely small for such categories, as is reflected in the very high values for the ratios. Such categories, however, are characterized by decreases of price sensitivity during contractions. Although consumers' budgets are tighter during contractions, price may become even less important in relative terms compared to expansions. Reducing the risk of buying a wrong product is more than ever a dominant concern in uncertain times, and consumers will consequently engage in even more profound information gathering and decision making, in which price will receive less weight relative to more functional aspects of the product.

Long run marketing effectiveness

Long run effectiveness, as (III.8) and (III.9) show, depends on the short run effectiveness of the marketing mix instruments and the carry-over effect of sales. We therefore first report the estimation results for carry-over.

Carry-over. As reported in table III.5, estimated carry-over effects are rather small ($\overline{\lambda}_{1,0}$ = *0.535*). The effect, however, will be stronger for products for which consumers rely on simple effort-reducing heuristics like e.g. the last brand purchased ($\overline{\lambda}_{1,1}$ = *-0.203*). Carry-over effects, in addition, are significantly smaller during economic downturns ($\overline{\lambda}_{2,0}$ = *-0.051*), as consumers are likely to show stronger switching behavior and less consistent buying patterns for national brands during contractions (e.g. Chance and French, 1972; Block, 1977; Wakefield and Inman, 1993. No significant differences in the impact of economic downturns on carry-over could be found between high and low involvement products.

The resulting estimated values for the long run effectiveness of Advertising and Price are reported in table III.7. These are the estimates for an average product, implying a zero effect of Involvement.

Table III.7. Long run advertising and price effectiveness for an average product

	2.5th percentile	Median	97.5th percentile
Long run Advertising effectiveness Expansion	0.005	**0.007**	0.010
Δ Long run Advertising effectiveness $\beta_{adv,LR} - \beta^*_{adv,LR}$	-0.002	0.001	0.003
Long run Price effectiveness Expansion	-2.617	**-2.306**	-2.018
Δ Long run Price effectiveness $\beta_{price,LR} - \beta^*_{price,LR}$	-0.107	0.054	0.193

Long run effects are about double the size of short run effects (*Advertising: 0.007 vs 0.003; Price: -2.306 vs -1.075*). Although we find decreases in long run advertising effects ($\beta_{adv,LR} - \beta^*_{adv,LR}$ = *0.001*) and increases in long run price effects

($\beta_{price,LR} - \beta^*_{price,LR}$ = *0.054*) during contractions versus expansions, none of these changes is significant. Whereas the tactical implications of marketing mix decisions are hence altered by the position in the business cycle, long run strategic implications will stay fairly constant.

III.7. DISCUSSION

Summary

Although marketing effectiveness has been the subject of a wide stream of research, to the best of our knowledge, no study has investigated in a systematic way how general economic conditions may affect this effectiveness. We therefore investigated how advertising and price elasticities evolve across the business cycle, i.e. how they differ in contractions vs expansions. Further, we examined to what extent evolutions may be different for different levels of product involvement. Analyses were based on 163 branded products in 37 mature CPG categories in the UK, and this for a period of 15 years. We combined (i) monthly national sales data, (ii) monthly advertising data, (iii) data on economic activity, and (iv) consumer survey data.

Most of the hypothesized effects were supported, as was shown in table III.5. During contractions, consumers become more price sensitive. In addition, spending patterns will be less consistent, implying smaller brand loyalty. Advertising elasticities, however, do not seem to be affected by economic downturns. Such downturns, in addition, do not show a direct effect on the sales of the included products. As these are often purchased products which could be categorized as necessities, postponing purchases until the economy recovers is not an option. Finally, although short run effectiveness of price differs between expansions and contractions, the long run effectiveness of both advertising and price is not altered by differences in the general economic conditions.

Managerial implications

Firms are under increasing pressure to increase both the accountability and the effectiveness of their marketing investments. Our findings can help managers in choosing the right strategies when deciding on marketing investments across the business cycle.

During contractions, managers are especially hesitant on how to allocate their budgets over price reductions (by lowering the margins) and advertising actions. Answers to this question can be found in the framework developed by Dorfman and Steiner (1954). According to this framework, marketing budgets should be allocated relative to the ratios of the respective elasticities. We showed that, in the short run, most firms in the mature CPG categories under consideration can gain by reallocating their budgets to price reductions instead of advertising. Price elasticities generally increase during contractions, whereas advertising elasticities are not altered. The extent to which the relative allocation should be adjusted, in turn, depends on the level of Involvement of the product category, with lower Involvement categories requiring stronger budget shifts.

An important remaining question, however, is how these findings can be reconciled with observations that companies spending relatively more on advertising during economic downturns have better financial performance (Frankenberger & Graham, 2003; Srinivasan et al., 2005; Deleersnyder et al., 2009; Srinivasan and Lilien, 2009). Shifting budgets from advertising to price reductions appears a recommended tactical decision to increase sales in the short run. Long run effects, however, are not altered by the general economic conditions. Consequently, at the strategic level, based on long run ratios, relative budget allocation should not be modified. Companies staying closer to these long run ratios by not cutting back on relative advertising expenditures may hence show better financial performance, as stock prices are hypothesized to incorporate all long run performance information of the company. This effect, in addition, may be enhanced by stronger deviations by competing companies from their optimal relative allocation. Cutting back too much on advertising may damage the brand in the long run, an effect which can be exacerbated by a lowering price image among customers when spending too much on price reductions. In addition, as advertising effectiveness as such does not change over the business cycle, extra investments in advertising can be expected to increase the company's results. Managers should consequently decide to what extent they consider marketing investments short run tactical means versus long run strategic investments. In the latter case, permanent evaluation and adjustment of the relative allocation of means is not needed. If, on the other hand, short run sales gains are the target, then a good understanding of the general economic situation in combination with changes in relative allocation becomes warranted.

Directions for future research

In our analyses of advertising and price elasticities, we based ourselves on a partial adjustment model specification. We believe this choice was warranted as such specification allows us to capture in a parsimonious way both short- and long-run effects of the different marketing mix instruments. A drawback of this choice for parsimony is the fact that we do not allow for instrument-specific carry-over effects. Alternative model specifications could hence allow for instrument-specific carry-over effects, or could be based on e.g. a Koyck specification. A comparison of our findings with the outcomes of such models would certainly add to the value of our work.

In this work, we analyzed advertising and price elasticities for a wide set of products and categories. We thereby focused on the 5 most important branded products per category, provided that they were on the market for at least 95% of the time. As such, we could expand our dataset in four ways: (i) allow for smaller brands, (ii) allow for private labels, (iii) investigate less mature categories, and (iv) examine durables.

First, we could enlarge our dataset by also including smaller brands in our analyses. However, in order to cover multiple business cycles and not to base our findings on the artifacts of just one cycle, brands have to be on the market long enough. As smaller brands may have more difficulties in complying with this condition, we opted to focus ourselves to the top 5. Further research in this direction hence appears warranted.

Second, we only focused on branded products. Examining to what extent marketing mix effectiveness varies over the business cycle for private labels makes up an interesting avenue for future research, especially given their remarkable and persistent market share gains during contractions (Lamey et al., 2007).

Third, our analyses are based on mature CPG categories. Such products are characterized by very small advertising elasticities (e.g. Sethuraman and Tellis, 1991). Less mature categories, on the other hand, can be expected to show stronger advertising sensitivity. In addition, this sensitivity may also vary more with the overall economic sentiment. Future research could hence include such products.

Finally, the products in our dataset are mainly every day necessities. Purchases cannot really be postponed until the economy recovers. This, on the other hand, is not the case for durables. Consumers can and do wait until the economic conditions improve and the uncertainty diminishes (Deleersnyder et al., 2004). This could result in even stronger business cycle effects on marketing mix effectiveness. A deeper investigation into this issue is hence called for.

IV

GENERAL DISCUSSION

More than ever, marketing investments are under pressure. Firms increasingly stress the need to improve the performance and accountability of their marketing investments. The recent economic downturn has invigorated this trend, as every dollar matters more in such circumstances. Measuring, understanding and improving the effectiveness of marketing investments has thus become of central interest to marketing managers, as they are increasingly summoned to justify these investments. This dissertation was built around one of the crucial determinants of the success of such marketing investments, i.e. their timing. A better understanding of its role in marketing decisions and effectiveness should enable firms to develop more effective strategies to increase their performance and returns, both in the short run and the long run. We therefore studied its role in two different, yet intertwined, dimensions: at the micro-level of individual campaigns, and at the macro-level across business cycles.

The outcome of individual advertising campaigns is to a large extent determined by the timing and magnitude of these campaigns (e.g. Danaher et al., 2008). The Industrial Economics literature has shown that firms' decisions and the resulting behavior and performance are primarily influenced by factors such as firm size (e.g. Cohen and Levin, 1989 p. 1067), competitors' (expected) behavior (e.g. Fudenberg and Tirole, 1989 p. 259), market concentration (e.g. Schmalensee, 1989 p. 996), and collusion tendencies (e.g. Jacquemin and Slade, 1989 p. 415). These factors, in turn, could be regrouped under (i) company-, (ii) competitor- , and (iii) category-related factors. Marketing decisions are no exception to this, and the same factors have also been shown to influence firms' marketing behavior (e.g. Metwally, 1978; Gatignon et al., 1990; Armstrong and Collopy, 1996; Montgomery et al., 2005). This work therefore investigated how firms' decisions on timing and magnitude of individual advertising campaigns are formed, and to what extent a number of these factors systematically influence those decisions.

The results of these micro-level advertising decisions, however, may not only depend on the optimality of the set-up of the individual campaign. They may as well be shaped by the moment in time at which these actions take place. Macro-economic conditions have been shown to be a particularly influential factor in marketing budget decisions. Marketing budgets, and especially advertising budgets, are among the first to be cut when the economy turns sour (e.g. Deleersnyder et al., 2009). Our data show that such advertising budget reductions are mostly characterized by reductions in the intensity of individual actions, although we also observe an overall frequency reduction. However, as this work shows, not only the magnitude of marketing investments depends on the timing of these investments, marketing effectiveness as well can be affected by investment timing. Although advertising effectiveness appears not to be altered by the general economic conditions, price elasticities and carry-over effects do show an evolution across the business cycle.

In the following sections, we briefly summarize the systematic conclusions that could be drawn from the empirical work presented in chapters II and III. We thereby first focus on the findings on marketing decisions on individual campaigns (micro-level), followed by those on marketing effectiveness across the business cycle (macro-level).

IV.1.THE ROLE OF TIMING AND MAGNITUDE IN ADVERTISING DECISIONS

Observed advertising spending patterns were shown to be mainly driven by internal company factors, with category and competitive factors having a much smaller impact or no impact, respectively. As such, timing and magnitude of advertising can to a large extent be considered the outcome of brands' advertising goodwill strategies. We were able to capture these dynamic strategies by embedding advertising and advertising goodwill in a well-known (s,S) inventory system.

Contrary to what has often been argued in the advertising literature, advertising decisions appear not to be influenced by competitive reasoning. A higher likelihood of competitive advertising will not lead to an increased likelihood of a new advertising action, or to higher expenditures. Escalation tendencies, with brands reacting on each others actions in an ever more fierce competition (e.g. Metwally, 1978) could consequently not be found. These results, on the other hand, complement the findings by Steenkamp et al. (2005) as their work also showed that reactions to sudden competitive advertising shocks are extremely rare. In tactical interactions, brands may prefer e.g. price promotions which have shown to be much more effective in engendering increased sales in the short run (e.g. Neslin, 2002; Steenkamp et al., 2005).

Decision processes on timing and magnitude of advertising campaigns are not equal for all types of brands. Brand market share and advertising frequency have been shown to be important determinants of the extent to which brands' advertising decisions can be described by means of advertising goodwill management systems. Larger brands can react better to changes in their advertising goodwill as they simply have more means at their disposal (Allenby and Hanssens, 2005). Learning effects through previous experience, in turn, may have shown higher frequency advertisers ways to monitor more closely the evolution of their advertising goodwill. These findings, at the same time, provide evidence of the importance of analyzing not only large and frequently acting brands. Results based on such analyses may be biased, given that these brands are only a small subset of the market, and consequently not representative for the market as a whole.

Although advertising decisions are not affected in a direct way by competitive actions and reactions, firms do base their behavior on more than just internal goodwill calculi. Timing and magnitude of advertising expenditures differ across categories. High growth categories show much stronger advertising behavior, with firms engaging more often in new advertising actions. These actions are also more intense than actions in low growth categories. Likely higher future profits in high growth categories thus invigorate the urge to create awareness and goodwill among consumers in order to become the preferred brand (Gatignon et al., 1990; Narayanan et al., 2005). Higher concentration within categories, on the other hand, makes firms refrain from advertising, possibly as a corollary of (implicit) collusive behavior. The more players in the market, the more likely firms will be to engage in new advertising actions. At the same time, however, they increase advertising clutter (Danaher et al., 2008), and thereby reduce advertising effectiveness.

Decision processes on timing and magnitude of advertising actions, although closely linked, are not only conceptually but also empirically different. Not only are they partly driven by different factors, common drivers also have different relative weights across the two decisions. Not allowing for these differences by not distinguishing between both decisions consequently causes a loss of information, and a less precise view, on which factors matter most in what part of the decision process.

IV.2. THE ROLE OF TIMING IN MARKETING EFFECTIVENESS

Advertising effectiveness has been argued to increase during contractions due to two phenomena. First, fewer competitors will be advertising, resulting in lower clutter, and second, media costs will be lower because of the laws of supply and (reduced) demand. Conversely, advertising effectiveness has also been argued to decrease during contractions as a result of two other phenomena. First, consumers have fewer means at their disposal to react to advertising messages, and second, they lose confidence and trust, important factors in consumers' willingness to purchase (Katona, 1975). In mature CPG categories, however, no such cyclical sensitivity of advertising effectiveness could be found.

Whereas no impact of the cyclical state of the economy could be found on advertising effectiveness, price sensitivity and carry-over effects do change. During economic contractions, price elasticities increase with about 14% on average. Consumers feel an increased pressure on their budgets, and become more price aware. They engage in more focused information search processes for lower price offers, thus trying to get the most out of their reduced budgets (e.g. Block, 1977; Wakefield and Inman, 1993). Consequently, lowering prices during downturns becomes a more rewarding short-run tactic for firms relative to investing in advertising. Whereas price sensitivity increases, behavioral brand loyalty, as reflected in purchase carry-over effects, decreases during contractions, at least for the national brands we considered. Purchase patterns become less consistent as consumers care more about the impact of their purchases on the means they have at their disposal. They evaluate more brands (e.g. Block, 1977; Wakefield and Inman, 1993), and are likely to switch to those brands offering a (temporarily) lower price.

However, these effects are not the same for all types of products. Product involvement, the subjective personal relevance of a certain product (Van Trijp et al., 1996), has a strong moderating effect on marketing effectiveness. Higher product involvement was shown to act as a buffer to marketing mix effectiveness. Higher involvement decisions require more elaborate information gathering and decision making processes. In these processes, each evaluated factor receives relatively less weight (Bloch et al., 1986; Assael, 1998). The effects of possible changes in effectiveness of individual marketing mix factors will consequently be smoothed by their relative low weight in the final decision. As a result, advertising elasticities and carry-over effects will be lower for higher involvement categories. During contractions, these factor smoothing effects of product involvement result in smaller increases of price sensitivity in higher involvement categories.

Although marketing-mix effectiveness is altered by the cyclical state of the economy in the short run, the associated long-run effects remain remarkably stable. This has far-reaching implications for firms. Based on the Dorfman-Steiner (1954) theorem for optimal marketing budget allocation, shifting budgets from advertising to price reductions is a rewarding tactical decision in the short run, as price reductions have become more effective. In the long run, however, the firm may benefit less from such changes. As the long-run effects of both marketing mix instruments are not altered by the general economic conditions, their relative attractiveness remains the same. Accordingly, relative budget allocation should not be altered. Adjusting budget allocation to the altered short-run ratios would hence lead to overspending on price reductions in the long run. Optimal short-run actions may thus result in sub-optimal long-run actions. These insights, on the other hand, are based on the assumption of constant marketing budgets. However, even when the relative allocation of budgets is based on the long-run ratios, reductions of marketing budgets during economic downturns can be expected to have a detrimental impact on firm performance.

IV.3. PATHWAYS FOR FUTURE RESEARCH

In this work, we provided several new insights which we believe contributed to the marketing literature. However, in the course of our work, our attention was drawn to several other issues that remain unresolved. As such, this dissertation is a starting point for further exploration. We elaborate on four such topics in the following sections: (i) Are the observed advertising spending patterns truly optimal for the brands? (ii) How are advertising campaigning decisions affected by the overall economic conditions? (iii) To what extent do our findings apply to private label products? (iv) How can more disaggregated media data add to our insights? Specific limitations of our two studies were already discussed at the end of the respective chapters. We therefore refer to these sections for a more detailed discussion on these limitations.

Optimality of advertising spending patterns

In the first essay of this dissertation, we investigated the timing and magnitude of advertising spending patterns. We posited that they could possibly be explained as an outcome of internal optimization calculi of individual firms (cfr. Doganoglu and Klapper, 2006), which in turn could (partly) be driven by decision heuristics (Tversky and Kahneman, 1974). However, we have no indications whether, or to what extent, the observed behavior was *truly* optimal for the firms under consideration. An alternative approach to the issue could therefore consist of the specification of a structural model for each individual brand (see e.g. Dubé et al., 2005). Similar to our work, these models rely on the view that observed behavior is the outcome of a profit maximization process of the individual firm, subject to resource constraints (Bronnenberg et al., 2005). Differing from our work, however, such structural models will explicitly specify the optimization calculus, thereby relying on economic theories and behavioral assumptions (Chintagunta et al., 2006). Starting from the specified calculus, optimal spending patterns can subsequently be derived.

The advantages of this structural approach are threefold. First, analyses will be less based on the data as such, and more on grounded economic theory (Chintagunta et al., 2006). Second, it can more easily account for structural changes in the market (Chintagunta et al.,2006). Third, it can in a clearer way model how both (i) consumers and (ii) competitors will react to firms' actions (Bronnenberg et al., 2005). However, this approach also shows some limitations. First, specification errors in the supply side (firms' decisions) can result in considerable biases in demand side estimates (consumers' reactions) (Bronnenberg et al., 2005). In addition, these models show significantly lower predictive validity relative to a reduced form model as we specified, especially in cases in which markets are rather stable (Bronnenberg et al., 2005; Chintagunta et al., 2006). Third, extensive data are needed to estimate all different parts of the specified model. Finally, structural models are derived from the assumption of optimal behavior relative to the information available to the firms. As such, they consider all agents to be extremely rational entities, thereby ignoring the fact that managers often rely on heuristics in their decision making (Tversky and Kahneman, 1974; Bronnenberg et al., 2005). These models thus perform well in predicting 'theoretical' optimal behavior, but perform less well in explaining observed behavior.

Given the relative advantages and drawbacks of both approaches, a comparison of their results would clearly add to the insights in what is driving advertising spending patterns, and whether the observed patterns are truly optimal for the advertising brands.

Advertising spending patterns over the business cycle

Our examination of advertising spending patterns focused on weekly advertising decisions of brands during a three-year period. We showed that firms' internal advertising goodwill management is a basic driver of the advertising decision process. However, in the course of our work on the cyclical sensitivity of marketing decisions and effectiveness, we learned that carry-over effects diminish during contractions. These carry-over effects, in turn, play a crucial role in the build-up of such advertising goodwill (e.g. Broadbent, 1984; Hanssens et al., 2001). In addition, during economic downturns, firms cut back on advertising expenditures (Deleersnyder et al., 2009). An interesting avenue for future research would therefore consist of an over time investigation on how advertising campaign decisions depend on the overall economic conditions, and whether brands show a differential behavior across expansions and contractions. What is the impact of lower carry-over during contractions? What are the consequences of lower advertising budgets? What causes the choice of smaller actions rather than fewer during contractions, as we observed in our data? How do the relative weights of the different drivers evolve? Will advertising goodwill management matter more or less during economic downturns?

Investigating the effects for private label products

Our work essentially focuses on marketing decisions and effectiveness of branded CPG products. However, these national brands increasingly experience competition by strong private labels that seemingly do not cease to gain market share (e.g. Steenkamp and Dekimpe, 1997; Kumar and Steenkamp 2007; Lamey et al., 2007). These private labels often cover many different product categories using the same brand name. Yet, not all categories receive the same attention and support from the retailers. As a consequence, marketing support will be stronger in a limited set of product categories. To what extent are advertising decisions in such a setting still driven by (s,S) advertising goodwill management strategies? Or do retailers follow other strategies? Product categories which receive less support may benefit from the increased support in the focal categories as they can benefit from the overall advertising goodwill of the retailer name. In addition, all categories could benefit from the weekly overall advertising by the retailer, even when not specifically directed to its own private label offerings. As such, the retailers' utility calculi and resulting decisions can be expected to differ from those of national brands.

The tendency towards increased market share for private labels is reinforced during economic contractions. Private labels show stronger and faster increases in market shares during such contractions, and smaller and slower decreases during expansions, resulting in overall market share gains (Lamey et al., 2007). One of the possible drivers behind this evolution could be an inverse effect of contractions on the carry-over effect for private labels relative to national brands. Whereas we found a decrease in carry-over for national brands, economic sour times could increase the consistency in consumers' preferences for private labels. As a result, carry-over effects can become stronger for private labels during downturns.

The days these private labels were nothing more but generic products, characterized by low price, low quality and zero image, in addition, are long gone. Over the years, private labels have shown a remarkable evolution. This has resulted in a clear differentiation between three types of private labels: (i) low-quality tier: economy private labels, fully focusing on the lowest price, (ii) mid-quality tier: standard private labels, offering average quality at a moderate price, and (iii) high-quality tier: premium private labels, focusing on quality (Kumar and Steenkamp 2007). Premium private labels, the most recent of these three types, are introduced in the same way as branded products. They are positioned as direct competitors of A-brands, and often do not carry the retailer name. Given their relative positioning, these three types of private labels are likely to react differently to changes in the economy. Price effectiveness, for instance, can be expected to evolve differently for economy private labels relative to premium private labels. The latter, in turn, may show more resemblance with their direct competitors, viz. the national brands.

In sum, given the seemingly unstoppable on-march of private labels, it would be of great value for national brands to understand (i) how advertising and pricing strategies of private labels are shaped, (ii) how marketing effectiveness of private label offerings evolves over the business cycle, and (iii) to what extent marketing decisions and effectiveness evolutions differ for different tiers of private labels. Insights on these issues could help brands in their attempts to fight back and preserve market share.

Media aggregation

Finally, our analyses were based on advertising expenditures aggregated over all different media. This, however, could mask several processes and effects.

When firms decide on advertising campaigns, they not only have to decide on the timing and magnitude of the campaign as a whole. They as well have to choose how to allocate their resources over different media. Firms thus basically face three important decisions when planning their advertising campaigns: (i) to advertise or not (*timing*), (ii) how much to spend (*magnitude*), and (iii) where to spend it (*media selection*) (Tellis, 2004 p. 72; Danaher, 2007 p. 645). Advertising effectiveness, however, may differ across media (Tellis, 2004). Moreover, for newer media like the Internet, it is still unclear (i) what makes up optimal spending, and (ii) how one should evaluate their effectiveness (Marketing Science Institute, 2008). Advertising media effectiveness, in addition, may also be different for different types of products (e.g. Kardes, 2002). This, in turn, is likely to result in a variation of media preferences over different brands and product types. Synergy effects between different media, in addition, can play a crucial role in the final decisions on the relative allocation of the assigned budgets (Naik and Raman, 2003). A closer investigation of the media choice in relation with the timing and magnitude of campaigns could consequently be an important contribution to our understanding of advertising campaigns.

Different media can not only be characterized by different effectiveness, this effectiveness may also behave differently over the business cycle. Based on aggregated media data, we did not find a significant change in advertising effectiveness. However, this aggregation could mask changes in individual media effectiveness, with some media becoming more effective, and others less effective. Knowing which media become more/less effective during economic downturns provides firms with guidelines on how to optimally spend their reduced advertising budgets.

The effectiveness evolution of these media may not only depend on the cyclical state of the economy. Advertising media effectiveness may as well be affected by two other phenomena: (i) increasing fragmentation of traditional media, and (ii) the introduction and rise of new advertising media. Increasing fragmentation of the traditional media – television and print media in particular – hampers their long-time main selling point: the reach of large populations at once (Rust and Oliver, 1994). At the same time, advertising clutter has dramatically increased. An average consumer is hit by up to 2,500 commercial imprints each day, and this number is still increasing (Bloom, 2003). The likely result of this evolution is an ever smaller advertising effectiveness of these media (cfr. Danaher et al., 2008). At the same time, the Internet rose as both an information and entertainment medium and as a new advertising medium. Its rise changed the media world even further (e.g. Rust & Varki, 1996; The Economist, 2006). Consumers spend ever more time in Internet-related activities. Firms, in turn, increasingly discover the Internet as an interesting advertising medium, resulting in larger budgets being allocated to Internet advertising (Advertising Age, 2007). However, as a possible corollary, consumers may also reduce their time spent on other media, thus reducing the latter's effectiveness even further. These media-world changes are challenging evolutions, to scholars and practitioners alike. It is therefore not surprising that (i) how and to what extent these new media can be interesting for advertisers, and (ii) what role older media retain in this new advertising media landscape, are also included in the 2008-2010 MSI Research Priorities (Marketing Science Institute, 2008). Consequently, a challenge for future research is to obtain a good understanding of how all these different factors affect the effectiveness of advertising investments over time, and which trends and cyclical components play which role in the effectiveness evolution.

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APPENDIX A

MATHEMATICAL DERIVATION OF AD-SENSOR

Ad-sensor captures the dynamics in the evolution of the brand's Adstock. This Adstock is defined as (Broadbent, 1984):

(A1) $$Adstock_{b,t} = (1-\lambda_b)Advert_{b,t} + \lambda_b Adstock_{b,t-1}$$

The first order condition for the optimum, i.e. the maximum Adstock level during a campaign, given that we use discrete time observations and we thus can only observe up to time t-1, is:

(A2) $$\frac{\Delta Adstock_{b,t-1}}{\Delta t} = 0$$

As we are analyzing discrete time data, this yields

(A3) $$\frac{Adstock_{b,t-1} - Adstock_{b,t-2}}{\Delta t} = 0$$

(A4) $$\Leftrightarrow Adstock_{b,t-1} - Adstock_{b,t-2} = 0.$$

Given (A1), this is satisfied if:

(A5) $$(1-\lambda_b)Advert_{b,t-1} + \lambda_b Adstock_{b,t-2} - Adstock_{b,t-2} = 0$$

(A6) $$\Leftrightarrow (1-\lambda_b)Advert_{b,t-1} = (1-\lambda_b)Adstock_{b,t-2}$$

(A7) $$\Leftrightarrow Advert_{b,t-1} = Adstock_{b,t-2}$$

The second order condition for this maximum at t-1 then requires:

(A8) $$Advert_{b,t-2} > Adstock_{b,t-3}.$$

because Adstock will increase as long as Advertising is larger than Adstock:

(A9) $Adstock_{b,t-1} > Adstock_{b,t-2}$

(A10) $\Leftrightarrow (1-\lambda_b)Advert_{b,t-1} + \lambda_b Adstock_{b,t-2} > Adstock_{b,t-2}$

(A11) $\Leftrightarrow (1-\lambda_b)Advert_{b,t-1} > (1-\lambda_b)Adstock_{b,t-2}$

(A12) $\Leftrightarrow Advert_{b,t-1} > Adstock_{b,t-2}$

The starting point for our Ad-sensor at time t is hence:

(A13) $Advert_{b,t-1} - Adstock_{b,t-2}$ > 0 if the maximum is reached after time t-1;
= 0 if the maximum is reached in t-1;
< 0 if the maximum was reached before t-1.

We subsequently rewrite (A1) in function of $Advert_{b,t-1}$:

(A14) $$Advert_{b,t-1} = \frac{Adstock_{b,t-1} - \lambda_b Adstock_{b,t-2}}{(1-\lambda_b)},$$

which yields:

(A15) $$Advert_{b,t-1} - Adstock_{b,t-2} = \frac{Adstock_{b,t-1} - \lambda_b Adstock_{b,t-2}}{(1-\lambda_b)} - Adstock_{b,t-2}$$

(A16) $$\approx Adstock_{b,t-1} - \lambda_b Adstock_{b,t-2} - (1-\lambda_b)Adstock_{b,t-2}$$

or

(A13) $$Advert_{b,t-1} - Adstock_{b,t-2} \approx Adstock_{b,t-1} - Adstock_{b,t-2}$$

We therefore define our Ad-sensor variable as the difference between Adstock in time *t*-1 and Adstock in *t*-2:

(A17) $$Adsensor_{b,t} = Adstock_{b,t-1} - Adstock_{b,t-2}$$

Ad-sensor thus captures the dynamics in the evolution of a brand's Adstock. In the beginning of a campaign, Adstock will increase very fast, causing high values of Ad-sensor. Closer to the maximum, increases will become smaller as Adstock approaches the Advertising values. As a consequence, the value of Ad-sensor starts to decrease. Once beyond the maximum, Adstock starts to decline, and Ad-sensor takes relatively strong negative values. Adstock decays at a constant rate λ, but not in constant absolute terms. When Adstock levels are still high, decay will be large in absolute terms, causing strong negative Ad-sensor values. Over time, the Adstock level becomes smaller, and decay will be smaller in absolute terms. The Ad-sensor values will become less negative, indicating a growing pressure to start advertising again.

APPENDIX B

NUMERICAL EXAMPLE OF ADSTOCK AND AD-SENSOR DEVELOPMENT

Week	Advertising	Adstock	Ad-sensor	s	S
1	0.00	0.00	0.00	5.00	197.65
2	0.00	0.00	0.00	5.00	197.65
3	0.00	0.00	0.00	5.00	197.65
4	120.00	36.00	0.00	5.00	197.65
5	200.00	85.20	36.00	5.00	197.65
6	240.00	131.64	49.20	5.00	197.65
7	230.00	161.15	46.44	5.00	197.65
8	240.00	184.80	29.51	5.00	197.65
9	210.00	192.36	23.66	5.00	197.65
10	210.00	197.65	7.56	5.00	197.65
11	190.00	195.36	5.29	5.00	197.65
12	110.00	169.75	-2.31	5.00	197.65
13	80.00	142.83	-25.61	5.00	197.65
14	50.00	114.98	-26.93	5.00	197.65
15	0.00	80.48	-27.85	5.00	197.65
16	0.00	56.34	-34.49	5.00	197.65
17	0.00	39.44	-24.15	5.00	197.65
18	0.00	27.61	-16.90	5.00	197.65
19	0.00	19.32	-11.83	5.00	197.65
20	0.00	13.53	-8.29	5.00	197.65
21	0.00	9.47	-5.80	5.00	197.65
22	0.00	6.63	-4.06	5.00	197.65
23	0.00	4.64	-2.84	5.00	197.65
24	0.00	3.25	*-1.99*	5.00	197.65
25	0.00	2.27	*-1.39*	5.00	197.65

We first simulate an average advertising campaign. These advertising expenditures are given in the second column. We subsequently calculate the Adstock (with imposed carry-over $\lambda = 0.70$) and Ad-sensor series.

For period 6, these are:

Adstock6 = (1-0.70)*240.00+0.70*85.20 = 131.64

Ad-sensor6 = 85.20-36.00 = 49.20

For period 11, these are:

Adstock11 = (1-0.70)*190.00+0.70*197.65 = 195.36

Ad-sensor11 = 197.65-192.36 = 5.29

For period 12, these are:

Adstock12 = (1-0.70)*110.00+0.70*195.36= 169.75

Ad-sensor12 = 195.36-197.65 = -2.31

For period 15, these are:

Adstock15 = (1-0.70)*0.00+0.70*114.98 = 80.48

Ad-sensor15 = 114.98-142.83 = -27.85

For period 16, these are:

Adstock16 = (1-0.70)*0.00+0.70*80.48 = 56.34

Ad-sensor16 = 80.48-114.98 = -34.49

For period 20, these are:

Adstock20 = (1-0.70)*0.00+0.70*19.32 = 13.53

Ad-sensor20 = 19.32-27.61 = -8.29

The highest observed Adstock level in this series equals 197.65. We consequently assume that this was the desired maximum level S. In this simulation, we impose s=5. In practice, we do not know s and S, and derive these from the observed patterns. In addition, we estimate λ for each individual brand.

APPENDIX C

MCMC ESTIMATION OF A HIERARCHICAL MULTIVARIATE TYPE-2 TOBIT MODEL

We will first briefly repeat the model specification.

An advertising decision in category c by brand b in week t (z_{cbt}) is described by a multivariate probit model:

(C1) $$z_{cbt} = \begin{cases} 1 \ \textit{if} \ z^*_{cbt} > 0 \\ 0 \ \textit{otherwise} \end{cases}$$

The latent variable z^*_{cbt} is modeled through a linear model:

(C2) $$z^*_{cbt} = \mathbf{x}'_{1cbt}\boldsymbol{\zeta}_{1cb} + \mathbf{x}'_{2cbt}\boldsymbol{\zeta}_{2cb} + \mu_{cbt}$$

Conditional on the decision to advertise (z_{cbt} = 1), we model y_{cbt}, the ln of spending by brand b in category c during week t as:

(C3) $$y_{cbt} = \mathbf{v}'_{1cbt}\boldsymbol{\omega}_{1cb} + \mathbf{v}'_{2cbt}\boldsymbol{\omega}_{2cb} + \varepsilon_{cbt}\,.$$

where

(C4) $$(\boldsymbol{\varepsilon}'_{ct}, \boldsymbol{\mu}'_{ct})' \sim MVN(0, \boldsymbol{\Sigma})$$

We relate the response parameters $\boldsymbol{\zeta}_{1cb}$ and $\boldsymbol{\omega}_{1cb}$ to a set of second stage variables.

(C5) $$\boldsymbol{\zeta}_{1cb} = \mathbf{Q}_{cb}\overline{\boldsymbol{\zeta}} + \mathbf{u}_{cb}$$

(C6) $$\boldsymbol{\omega}_{1cb} = \mathbf{R}_{cb}\overline{\boldsymbol{\omega}} + \mathbf{e}_{cb}$$

where

(C7) $$(\mathbf{e}'_{cb}, \mathbf{u}'_{cb})' \sim MVN(0, \boldsymbol{\Omega})\,.$$

We stack (i) the dependent variables of equations (C2) and (C3) for all brands b in category c and time periods t so that the vector of ln expenditures is $\mathbf{y}_c = [y_{c11}, y_{c12}, \ldots, y_{cB_cT}]'$ and the vector of advertising action indicator variables is $\mathbf{z}^*_c = [z^*_{c11}, z^*_{c12}, \ldots, z^*_{cB_cT}]'$, (ii) the predictor variables for the advertising action equation, $\mathbf{v}'_{1cbt}$ = [$v_{1cb1t}, v_{1cb2t}, \ldots, v_{1cbMt}$]′ and $\mathbf{v}'_{2cbt}$ = [$v_{2cb1t}, v_{2cb2t}, \ldots, v_{2cbMt}$]′ ; the predictor variables for the ln expenditures equation, $\mathbf{x}'_{1cbt}$ = [$x_{1cb1t}, x_{1cb2t}, \ldots, x_{1cbMt}$]′ and $\mathbf{x}'_{2cbt}$ = [$x_{2cb1t}, x_{2cb2t}, \ldots, x_{2cbMt}$]′; and (iii) the error terms of these two equations for all brands b and time periods t so that $[\boldsymbol{\varepsilon}'_{ct}, \boldsymbol{\mu}'_{ct}]'$= [$\varepsilon_{c1t}, \varepsilon_{c2t}, \ldots, \varepsilon_{cB_ct}$, $\mu_{c1t}, \mu_{c2t}, \ldots, \mu_{cB_ct}$]′ follows a $(2B_c)$-variate normal distribution with zero mean and full covariance matrix

$$\Sigma_{\mathbf{c}} = \begin{bmatrix} \boldsymbol{\Sigma}_{c11} & \boldsymbol{\Sigma}_{c12} \\ \boldsymbol{\Sigma}'_{c12} & \boldsymbol{\Sigma}_{c22} \end{bmatrix}$$

where $\boldsymbol{\Sigma}_{c11} = E(\boldsymbol{\varepsilon}_{ct}\boldsymbol{\varepsilon}'_{ct})\forall c$, $\boldsymbol{\Sigma}_{c12} = E(\boldsymbol{\varepsilon}_{ct}\boldsymbol{\mu}'_{ct})\forall c$, and $\boldsymbol{\Sigma}_{c22} = E(\boldsymbol{\mu}_{ct}\boldsymbol{\mu}'_{ct})\forall c$, which has ones on the diagonal since each selectivity mechanism is binary.

Next we specify the hierarchies associated with the two advertising decisions. We stack (i) the parameter coefficients per category and per brand across equations (C2) and (C3) and (ii) the error terms of the hierarchical equations for all brands b in a similar way. We model the response parameters as follows:

$$\begin{bmatrix} \boldsymbol{\omega}_{1c1} \\ \zeta_{1c1} \\ \boldsymbol{\omega}_{1c2} \\ \zeta_{1c2} \\ \vdots \\ \boldsymbol{\omega}_{1cB_c} \\ \zeta_{1cB_c} \end{bmatrix} = \begin{bmatrix} \mathbf{Q}_{c1} & \\ & \mathbf{R}_{c1} \\ \mathbf{Q}_{c2} & \\ & \mathbf{R}_{c2} \\ & \vdots \\ \mathbf{Q}_{cB_c} & \\ & \mathbf{R}_{cB_c} \end{bmatrix} \begin{bmatrix} \overline{\boldsymbol{\omega}} \\ \overline{\zeta} \end{bmatrix} + \begin{bmatrix} \mathbf{e}_{c1} \\ \mathbf{u}_{c1} \\ \mathbf{e}_{c2} \\ \mathbf{u}_{c2} \\ \vdots \\ \mathbf{e}_{cB_c} \\ \mathbf{u}_{cB_c} \end{bmatrix}, \begin{bmatrix} \mathbf{e}_{c1} \\ \mathbf{u}_{c1} \\ \mathbf{e}_{c2} \\ \mathbf{u}_{c2} \\ \vdots \\ \mathbf{e}_{cB_c} \\ \mathbf{u}_{cB_c} \end{bmatrix} \sim N_{|\mathbf{u}_c|+|\mathbf{e}_c|}\left(0, \mathbf{I}_{B_c} \otimes \boldsymbol{\Omega}\right),$$

with $\mathbf{Q}_{cb}$ = $\mathbf{R}_{cb}$ = $\mathbf{I}_M \otimes \mathbf{q}'_{cb}$, where $\mathbf{I}_M$ is an (M x M) identity matrix and $\mathbf{q}'_{cb}$ is a 1 x (N/M) vector of covariates. The hyperparameters relating these covariates to the actual first level response parameters are stacked in $[\overline{\boldsymbol{\omega}}'\ \overline{\boldsymbol{\zeta}}']'$=
$\lfloor \omega_{11,1}, \omega_{11,2} \ldots \omega_{11,N/M}, \omega_{12,1} \ldots \omega_{1M,N/M}, \zeta_{11,1}, \zeta_{11,2} \ldots \zeta_{11,N/M}, \zeta_{12,1} \ldots \zeta_{1M,N/M} \rfloor$, with $\overline{\boldsymbol{\omega}}$ and $\overline{\zeta}$ both being (N x 1) vectors.

$\mathbf{\Omega} = \begin{bmatrix} \mathbf{\Omega}_{11} & \mathbf{\Omega}_{12} \\ \mathbf{\Omega}_{12}^{'} & \mathbf{\Omega}_{22} \end{bmatrix}$ is a full covariance matrix where $\mathbf{\Omega}_{11} = E(\mathbf{e}_{cb}\mathbf{e}_{cb}^{'})\forall c, b$,

$\mathbf{\Omega}_{12} = E(\mathbf{e}_{cb}\mathbf{u'}_{cb})\forall c, b$, and $\mathbf{\Omega}_{22} = E(\mathbf{u}_{cb}\mathbf{u'}_{cb})\forall c, b$.

We use an MCMC approach to estimate the marginal distributions of the latent dependent variables, parameters and covariances. The MCMC algorithm involves sampling sequentially from the relevant conditional distributions over a large number of iterations. These draws can be shown to converge to the marginal posterior distributions. Our implementation of the MCMC algorithm has 6 steps that are described below.

Conditional distributions

The first implementation step requires that we specify conditional distributions of the relevant variables. The solutions of these distributions follow from the normality assumption of the disturbances terms. We employ natural conjugate priors. Specifications of the conditional distributions are as follows:

1. $\mathrm{y}^{*}_{\mathrm{cbt}}$ is y_{cbt} if z_{cbt} =1, otherwise $\mathrm{y}^{*}_{\mathrm{cbt}}$ is drawn from a normal distribution:

$$y^{*}_{cbt} \left| \mathbf{y}^{*}_{c,j\neq b,t}, \mathbf{z}^{*}_{ct}, \mathbf{\omega}_{cb}, \alpha_{cb}, \iota_{cb} \, \Sigma \right.$$

$$\sim \begin{cases} y_{cbt} \left| z_{cbt} \right. = 1 \\ N(\mathbf{v}'_{1cbt}\mathbf{\omega}_{1cb} + \mathbf{v}'_{2cbt}\mathbf{\omega}_{2cb} + \mathbf{\sigma}_{cb,cj}\widetilde{\mathbf{\Sigma}}^{-1}_{cj,cj}\begin{pmatrix} \mathbf{y}^{*}_{c,j\neq b,t} - \mathrm{E}(\mathbf{y}^{*}_{c,j\neq b,t}) \\ \mathbf{z}^{*}_{c,t} - \mathrm{E}(\mathbf{z}^{*}_{ct}) \end{pmatrix}, \sigma^{(11)}_{cb,cb} - \mathbf{\sigma'}_{cb,cj}\widetilde{\mathbf{\Sigma}}^{-1}_{cj,cj}\mathbf{\sigma}_{cj,cb}) \,|\, \left| z_{cbt} \right. = 0 \end{cases}$$

where $\mathbf{y}^{*}_{ct} = \begin{bmatrix} y^{*}_{cbt} \\ -- \\ \mathbf{y}^{*}_{c,j\neq b,t} \end{bmatrix}$ and $\mathbf{\Sigma}_{c} = \begin{bmatrix} \sigma^{(11)}_{cb,cb} & | & \mathbf{\sigma'}_{cb,cj} \\ -- & & -- \\ \mathbf{\sigma}_{cj,cb} & | & \widetilde{\mathbf{\Sigma}}_{cj,cj} \end{bmatrix}$

As the notation suggests, the $\mathbf{y}^{*}_{ct}$ vector and $\Sigma_{\mathbf{c}}$ matrix are partitioned between the brand of interest, *cb*, and all other brands *cj*, $j \neq b$ (the entries in $\Sigma_{\mathbf{c}}$ corresponding to **z** are not shuffled). Without loss of generality, we have assumed the brand of interest to be the first. Each brand is then drawn in succession for category c, conditioning on $\mathbf{y}^{*}_{c,j\neq b,t}$, $\mathbf{z}^{*}_{ct}$, and $\Sigma_{\mathbf{c}}$.

2. We next draw the latent dependent variable values for the probit component of the model. If the indicator variable z_{cbt} = 1, then z^{*}_{cbt} is drawn from a normal distribution, truncated below at 0. Otherwise, z^{*}_{cbt} is drawn from a normal distribution, truncated above at 0.

$$\mathbf{z}^{*}_{cbt} \left| \mathbf{z}^{*}_{c,j\neq b,t}, \mathbf{y}^{*}_{ct}, \boldsymbol{\zeta}_{cb}, \alpha_{cb}, \iota_{cb}, \boldsymbol{\Sigma} \right.$$

$$\sim N_T \left(\mathbf{x}'_{c1bt}\boldsymbol{\zeta}_{1cb} + \mathbf{x}'_{2cbt}\boldsymbol{\zeta}_{2cb} + \sigma_{cb,cj}\tilde{\boldsymbol{\Sigma}}^{-1}_{cj,cj} \begin{pmatrix} \mathbf{z}^{*}_{c,j\neq b,t} - \mathrm{E}(\mathbf{z}^{*}_{c,j\neq b,t}) \\ \mathbf{y}^{*}_{c,t} - \mathrm{E}(\mathbf{y}^{*}_{ct}) \end{pmatrix}, \sigma_{cb,cb} - \boldsymbol{\sigma}'_{cb,cj}\tilde{\boldsymbol{\Sigma}}^{-1}_{cj,cj}\boldsymbol{\sigma}_{cj,cb} \right)$$

where: $z^{*}_{ct} = \begin{bmatrix} z^{*}_{cbt} \\ -- \\ \mathbf{z}^{*}_{c,j\neq b,t} \end{bmatrix}$ and $\boldsymbol{\Sigma}_c = \begin{bmatrix} \sigma^{(22)}_{cb,cb} & | & \boldsymbol{\sigma}'_{cb,cj} \\ -- & & -- \\ \boldsymbol{\sigma}_{cj,cb} & | & \tilde{\boldsymbol{\Sigma}}_{cj,cj} \end{bmatrix}$

The latent probit dependent variables are drawn using the inverse cdf method.

3. The parameters in $\left[\boldsymbol{\omega}_{1c1}, \boldsymbol{\zeta}_{1c1,}\boldsymbol{\omega}_{1c2}, \boldsymbol{\zeta}_{1c2}, \ldots, \boldsymbol{\omega}_{1cB_c}, \boldsymbol{\zeta}_{1cB_c,}\right]'$ are drawn from a SUR model with variance/covariance matrix of disturbances $\boldsymbol{\Sigma}_c$:

$$\begin{bmatrix} \boldsymbol{\omega}_{1c1} \\ \boldsymbol{\zeta}_{1c1} \\ \boldsymbol{\omega}_{1c2} \\ \boldsymbol{\zeta}_{1c2} \\ \vdots \\ \boldsymbol{\omega}_{1cB_c} \\ \boldsymbol{\zeta}_{1cB_c} \end{bmatrix} \left| \mathbf{y}^{*(t)}, \mathbf{z}^{*(t)}, \boldsymbol{\Sigma}^{(t-1)}_c \right. \sim N \left(\mathbf{O}_c \left(\mathbf{P}'_{1c}\left(\mathbf{I}_{T_c} \otimes \boldsymbol{\Sigma}^{-1}_{\mathrm{c}}\right) \begin{bmatrix} y^{*(t)}_{c11} - \mathbf{v}'_{2c11}\boldsymbol{\omega}_{2c1} \\ z^{*(t)}_{c11} - \mathbf{x}'_{2c11}\boldsymbol{\zeta}_{2c1} \\ y^{*(t)}_{c21} - \mathbf{v}'_{2c21}\boldsymbol{\omega}_{2c2} \\ z^{*(t)}_{c21} - \mathbf{x}'_{2c21}\boldsymbol{\zeta}_{2c2} \\ \vdots \\ y^{*(t)}_{cB_c1} - \mathbf{v}'_{2cB_c1}\boldsymbol{\omega}_{2cB_c} \\ z^{*(t)}_{cB_c1} - \mathbf{x}'_{2cB_c1}\boldsymbol{\zeta}_{2cB_c} \\ y^{*(t)}_{c12} - \mathbf{v}'_{2c12}\boldsymbol{\omega}_{2c1} \\ z^{*(t)}_{c12} - \mathbf{x}'_{2c12}\boldsymbol{\zeta}_{2c1} \\ \vdots \\ y^{*(t)}_{cB_cT_c} - \mathbf{v}'_{2cB_cT_c}\boldsymbol{\omega}_{2cB_c} \\ z^{*(t)}_{cB_cT_c} - \mathbf{x}'_{2cB_cT_c}\boldsymbol{\zeta}_{2cB_c} \end{bmatrix} + \left[\mathbf{I}_{B_c} \otimes \boldsymbol{\Omega}^{-1}\right] \begin{bmatrix} \mathbf{Q}_{c1} & & & \\ & \mathbf{R}_{c1} & & \\ & & \mathbf{Q}_{c2} & \\ & & & \mathbf{R}_{c2} \\ & & \ddots & \\ & \mathbf{Q}_{cB_c} & & \\ & & & \mathbf{R}_{cB_c} \end{bmatrix} \begin{bmatrix} \overline{\boldsymbol{\omega}} \\ \overline{\boldsymbol{\zeta}} \end{bmatrix} \right), \mathbf{O}_c \right)$$

$$
\text{where } \boldsymbol{\Sigma}_c = \begin{bmatrix}
\sigma_{y_{c1}y_{c1}} & \sigma_{y_{c1}z_{c1}} & \sigma_{y_{c1}y_{c2}} & \sigma_{y_{c1}z_{c2}} & \cdots & \sigma_{y_{c1}y_{cB_c}} & \sigma_{y_{c1}z_{cB_c}} \\
\sigma_{z_{c1}y_{c1}} & \sigma_{z_{c1}z_{c1}} & \sigma_{z_{c1}y_{c2}} & \sigma_{z_{c1}z_{c2}} & & \sigma_{z_{c1}y_{cB_c}} & \sigma_{z_{c1}z_{cB_c}} \\
\sigma_{y_{c2}y_{c1}} & \sigma_{y_{c2}z_{c1}} & \sigma_{y_{c2}y_{c2}} & \sigma_{y_{c2}z_{c2}} & & & \\
\sigma_{z_{c2}y_{c1}} & \sigma_{z_{c2}z_{c1}} & \sigma_{z_{c2}y_{c2}} & \sigma_{z_{c2}z_{c2}} & & & \\
\vdots & & & & \ddots & & \\
\sigma_{y_{cB_c}y_{c1}} & \sigma_{y_{cB_c}z_{c1}} & & & & \sigma_{y_{cB_c}y_{cB_c}} & \sigma_{y_{cB_c}z_{cB_c}} \\
\sigma_{z_{cB_c}y_{c1}} & \sigma_{z_{cB_c}z_{c1}} & & & & \sigma_{z_{cB_c}y_{cB_c}} & \sigma_{z_{cB_c}z_{cB_c}}
\end{bmatrix},
$$

$$
\text{and} \quad \mathbf{O}_c = \left(\mathbf{P}_{1c}^{'}\left(\mathbf{I}_{T_c} \otimes \boldsymbol{\Sigma}_c^{-1(t-1)}\right)\mathbf{P}_{1c} + \mathbf{I}_{B_c} \otimes \boldsymbol{\Omega}^{-1}\right)^{-1},
$$

$$
\text{and} \quad \mathbf{P}_{1c} = \begin{bmatrix}
\mathbf{v}_{1c11}^{'} & & & & & & \\
& \mathbf{x}_{1c11}^{'} & & & & & \\
& & \mathbf{v}_{1c21}^{'} & & & & \\
& & & \mathbf{x}_{1c21}^{'} & & & \\
& & & & \ddots & & \\
& & & & & \mathbf{v}_{1cB_c1}^{'} & \\
& & & & & & \mathbf{x}_{1cB_c1}^{'} \\
\mathbf{v}_{1c12}^{'} & & & & & & \\
& \mathbf{x}_{1c12}^{'} & & & & & \\
& & \mathbf{v}_{1c22}^{'} & & & & \\
& & & \mathbf{x}_{1c22}^{'} & & & \\
& & & & \ddots & & \\
& & \vdots & & & \mathbf{v}_{1cB_c2}^{'} & \\
& & & & & & \mathbf{x}_{1cB_c2}^{'} \\
\mathbf{v}_{1c1T_c}^{'} & & & & & & \\
& \mathbf{x}_{1c1T_c}^{'} & & & & \vdots & \\
& & \mathbf{v}_{1c2T_c}^{'} & & & & \\
& & & \mathbf{x}_{1c2T_c}^{'} & & & \\
& & & & \ddots & & \\
& & & & & \mathbf{v}_{1cB_cT_c}^{'} & \\
& & & & & & \mathbf{x}_{1cB_cT_c}^{'}
\end{bmatrix}.
$$

4. The vector of hyper-parameters, $\left[\bar{\boldsymbol{\omega}}', \bar{\zeta}'\right]'$, is drawn from a SUR model with variance/covariance matrix of disturbances

$$\boldsymbol{\Omega} : \begin{bmatrix} \bar{\boldsymbol{\omega}}^{(t)} \\ \bar{\zeta}^{(t)} \end{bmatrix} | \boldsymbol{\omega}^{(t)}, \boldsymbol{\zeta}^{(t)}, \boldsymbol{\Omega} \sim N\left(\mathbf{J}\left(\mathbf{S}'(\mathbf{I}_B \otimes \boldsymbol{\Omega}^{-1}) \begin{bmatrix} \boldsymbol{\omega}_{111} \\ \zeta_{111} \\ \boldsymbol{\omega}_{112} \\ \zeta_{112} \\ \vdots \\ \boldsymbol{\omega}_{11B_1} \\ \zeta_{11B_1} \\ \boldsymbol{\omega}_{121} \\ \zeta_{121} \\ \vdots \\ \boldsymbol{\omega}_{1CB_c} \\ \zeta_{1CB_c} \end{bmatrix} + \bar{\boldsymbol{\Omega}}^{-1} \begin{bmatrix} \bar{\bar{\boldsymbol{\omega}}} \\ \bar{\bar{\zeta}} \end{bmatrix} \right), \mathbf{J} \right),$$

where $\mathbf{J} = \left(\mathbf{S}'(\mathbf{I}_B \otimes \boldsymbol{\Omega}^{-1})\mathbf{S} + \bar{\boldsymbol{\Omega}}^{-1}\right)^{-1}$, $\mathbf{S} = \begin{bmatrix} \mathbf{Q}_{11} & \\ & \mathbf{R}_{11} \\ \mathbf{Q}_{12} & \\ & \mathbf{R}_{12} \\ & \vdots & \\ \mathbf{Q}_{1B_1} & \\ & \mathbf{R}_{1B_1} \\ \mathbf{Q}_{21} & \\ & \mathbf{R}_{21} \\ & \vdots & \\ \mathbf{Q}_{CB_C} & \\ & \mathbf{R}_{CB_C} \end{bmatrix}$,

with B the sum of all B_c and hence the total number of brands.

5. The vector of parameters, $\left[\boldsymbol{\omega}_{2c1},\boldsymbol{\zeta}_{2c1,}\boldsymbol{\omega}_{2c2},\boldsymbol{\zeta}_{2c2},\ldots,\boldsymbol{\omega}_{2cB_c},\boldsymbol{\zeta}_{2cB_c,}\right]'$, is drawn from a Bayesian regression model:

$$\begin{bmatrix}\boldsymbol{\omega}_{2c1}\\ \boldsymbol{\zeta}_{2c1}\\ \boldsymbol{\omega}_{2c2}\\ \boldsymbol{\zeta}_{2c2}\\ \vdots\\ \boldsymbol{\omega}_{2cB_c}\\ \boldsymbol{\zeta}_{2cB_c}\end{bmatrix}\Big|\boldsymbol{\omega}_1^{(t)},\boldsymbol{\zeta}_1^{(t)}\sim N\left(\mathbf{J}_{2c}\left(\mathbf{P}_{2c}{}'\left(\mathbf{I}_{T_c}\otimes\boldsymbol{\Sigma}_{\mathrm{c}}^{-1}\right)\begin{bmatrix}y_{c11}^{*(t)}-\mathbf{v}'_{1c11}\boldsymbol{\omega}_{1c1}\\ z_{c11}^{*(t)}-\mathbf{x}'_{1c11}\boldsymbol{\zeta}_{1c1}\\ y_{c21}^{*(t)}-\mathbf{v}'_{1c21}\boldsymbol{\omega}_{1c2}\\ z_{c21}^{*(t)}-\mathbf{x}'_{1c21}\boldsymbol{\zeta}_{1c2}\\ \vdots\\ y_{cB_c1}^{*(t)}-\mathbf{v}'_{1cB_c1}\boldsymbol{\omega}_{1cB_c}\\ z_{cB_c1}^{*(t)}-\mathbf{x}'_{1cB_c1}\boldsymbol{\zeta}_{1cB_c}\\ y_{c12}^{*(t)}-\mathbf{v}'_{1c12}\boldsymbol{\omega}_{1c1}\\ z_{c12}^{*(t)}-\mathbf{x}'_{1c12}\boldsymbol{\zeta}_{1c1}\\ \vdots\\ y_{cB_cT_c}^{*(t)}-\mathbf{v}'_{1cB_cT_c}\boldsymbol{\omega}_{1cB_c}\\ z_{cB_cT_c}^{*(t)}-\mathbf{x}'_{1cB_cT_c}\boldsymbol{\zeta}_{1cB_c}\end{bmatrix}+\overline{\boldsymbol{\Omega}}_2^{-1}\begin{bmatrix}\overline{\varpi}_2\\ \overline{\zeta}_2\end{bmatrix}\right),\mathbf{J}_{2c}\right),$$

where $\mathbf{J}_{2c}=\left(\mathbf{P}_{2c}{}'\left(\mathbf{I}_{T_c}\otimes\boldsymbol{\Sigma}_{\mathrm{c}}^{-1}\right)\mathbf{P}_{2c}+\overline{\boldsymbol{\Omega}}_2^{-1}\right)^{-1}$,

$$
\mathbf{P}_{2c} = \left[\begin{array}{ccccccc}
\mathbf{v}'_{2c11} & & & & & & \\
 & \mathbf{x}'_{2c11} & & & & & \\
 & & \mathbf{v}'_{2c21} & & & & \\
 & & & \mathbf{x}'_{2c21} & & & \\
 & & & & \ddots & & \\
 & & & & & \mathbf{v}'_{2cB_c1} & \\
 & & & & & & \mathbf{x}'_{2cB_c1} \\
\mathbf{v}'_{2c12} & & & & & & \\
 & \mathbf{x}'_{2c12} & & & & & \\
 & & \mathbf{v}'_{2c22} & & & & \\
 & & & \mathbf{x}'_{2c22} & & & \\
 & & & & \ddots & & \\
 & & \vdots & & & \mathbf{v}'_{2cB_c2} & \\
 & & & & & & \mathbf{x}'_{2cB_c2} \\
\mathbf{v}'_{2c1T_c} & & & & & & \\
 & \mathbf{x}'_{2c1T_c} & & & & \vdots & \\
 & & \mathbf{v}'_{2c2T_c} & & & & \\
 & & & \mathbf{x}'_{2c2T_c} & & & \\
 & & & & \ddots & & \\
 & & & & & \mathbf{v}'_{2cB_cT_c} & \\
 & & & & & & \mathbf{x}'_{2cB_cT_c}
\end{array}\right],
$$

6. $\boldsymbol{\Sigma}_c$ is drawn from an inverted Wishart distribution with $T_c+\nu_\Sigma$ degrees of freedom:

$$
\boldsymbol{\Sigma}_c^{-1(t)} \left| \boldsymbol{\omega}^{(t)}, \boldsymbol{\zeta}^{(t)}, \mathbf{y}^{*(t)}, \mathbf{z}^{*(t)}, \boldsymbol{\delta}^{(t)}, \boldsymbol{\psi}^{(t)}, \mathbf{V}^{(t)}, \mathbf{V}_{\Sigma_c}, \nu_{\Sigma_c} \right. \sim Wish\left(T_c + \nu_{\Sigma_c}, \left(\mathbf{V}_{\Sigma_c} + \begin{bmatrix} \boldsymbol{\varepsilon}_c \\ \boldsymbol{\mu}_c \end{bmatrix} \begin{bmatrix} \boldsymbol{\varepsilon}'_c & \boldsymbol{\mu}'_c \end{bmatrix} \right)^{-1} \right)
$$

7. $\boldsymbol{\Omega}$ is drawn from an inverted Wishart distribution with $B+\nu_\Omega$ degrees of freedom.

$$
\boldsymbol{\Omega}^{-1(t)} \left| \boldsymbol{\omega}^{(t)}, \overline{\boldsymbol{\omega}}^{(t)}, \boldsymbol{\zeta}^{(t)}, \overline{\boldsymbol{\zeta}}^{(t)}, \mathbf{V}_\Omega, \nu_\Omega \right. \sim Wish\left(B + \nu_\Omega, \left(\mathbf{V}_\Omega + \begin{bmatrix} \mathbf{e} \\ \mathbf{u} \end{bmatrix} \begin{bmatrix} \mathbf{e}' & \mathbf{u}' \end{bmatrix} \right)^{-1} \right).
$$

For identification purposes we need ones on the diagonal of incidence equation error matrix $\boldsymbol{\Sigma}_{c22} = E(\boldsymbol{\mu}_{ct}\boldsymbol{\mu}'_{ct})\forall c$ (while $\boldsymbol{\Sigma}_\mathbf{c}$ is positive definite), and we need to rescale the parameters from the incidence equation relative to $\boldsymbol{\Sigma}_{c22}$. To achieve this, we follow the procedure proposed by Edwards and Allenby (2003) and Rossi, Allenby, and McCulloch (2005, p. 108). That is, we do not impose any restrictions when drawing $\boldsymbol{\Sigma}_c$. Instead, we postprocess the draws using the following diagonal matrices:

$$\mathbf{C}_{c1} = \begin{bmatrix} \mathbf{I}_{B_c} & 0 \\ 0 & \mathrm{diag}(\boldsymbol{\Sigma}_{c22})^{-\frac{1}{2}} \end{bmatrix}, \forall c;$$

$$\mathbf{C}_{1c2} = \begin{bmatrix} \mathbf{I}_M & 0 & & & & & \\ 0 & (1/\sqrt{\boldsymbol{\Sigma}_{c22}^{(1,1)}})\cdot\mathbf{I}_M & & & & & \\ & & \mathbf{I}_M & 0 & & & \\ & & 0 & (1/\sqrt{\boldsymbol{\Sigma}_{c22}^{(2,2)}})\cdot\mathbf{I}_M & & & \\ & & & & \ddots & & \\ & & & & & \mathbf{I}_M & 0 \\ & & & & & 0 & (1/\sqrt{\boldsymbol{\Sigma}_{c22}^{(B_c,B_c)}})\cdot\mathbf{I}_M \end{bmatrix}, \forall c,$$

$$\mathbf{C}_{2c2} = \begin{bmatrix} \mathbf{I}_L & 0 & & & & & \\ 0 & (1/\sqrt{\boldsymbol{\Sigma}_{c22}^{(1,1)}})\cdot\mathbf{I}_L & & & & & \\ & & \mathbf{I}_L & 0 & & & \\ n & & 0 & (1/\sqrt{\boldsymbol{\Sigma}_{c22}^{(2,2)}})\cdot\mathbf{I}_L & & & \\ & & & & \ddots & & \\ & & & & & \mathbf{I}_L & 0 \\ & & & & & 0 & (1/\sqrt{\boldsymbol{\Sigma}_{c22}^{(B_c,B_c)}})\cdot\mathbf{I}_L \end{bmatrix}, \forall c,$$

$$\mathbf{C}_3 = \begin{bmatrix} \mathbf{I}_N & 0 \\ 0 & \mathrm{mean}(\mathrm{diag}(\boldsymbol{\Sigma}_{c22})^{-\frac{1}{2}})\cdot\mathbf{I}_N \end{bmatrix} \text{ and } \mathbf{C}_4 = \begin{bmatrix} \mathbf{I}_M & 0 \\ 0 & \mathrm{mean}(\mathrm{diag}(\boldsymbol{\Sigma}_{c22})^{-\frac{1}{2}})\cdot\mathbf{I}_M \end{bmatrix}$$

After completing the Gibbs chain, we calculate $\boldsymbol{\Sigma}_c^* = \mathbf{C}_{c1}\boldsymbol{\Sigma}_c\mathbf{C}'_{c1}$ for each saved Gibbs draw, monitor its convergence, and use it for inference purposes. Analogously, for inferences we use $(\boldsymbol{\omega}'_{1c}, \boldsymbol{\zeta}'_{1c})^{*\prime} = \mathbf{C}_{1c2}\cdot(\boldsymbol{\omega}'_{1c}, \boldsymbol{\zeta}'_{1c})', \forall c$; $(\boldsymbol{\omega}'_{2c}, \boldsymbol{\zeta}'_{2c})^{*\prime} = \mathbf{C}_{2c2}\cdot(\boldsymbol{\omega}'_{2c}, \boldsymbol{\zeta}'_{2c})', \forall c$; $(\overline{\boldsymbol{\varpi}}', \overline{\boldsymbol{\zeta}}')^{*\prime} = \mathbf{C}_3.(\overline{\boldsymbol{\varpi}}', \overline{\boldsymbol{\zeta}}')'$, and $\boldsymbol{\Omega}^* = \mathbf{C}_4\boldsymbol{\Omega}\mathbf{C}'_4$.

Prior distributions

The second implementation step is to specify prior distributions for the parameters of interest. Note that the priors are set to be non-informative so that inferences are driven by the data.

The prior distribution of $[\bar{\boldsymbol{\omega}}', \bar{\zeta}']'$ is $N([\bar{\bar{\boldsymbol{\omega}}}', \bar{\bar{\zeta}}']', \bar{\boldsymbol{\Omega}})$,

where $[\bar{\bar{\boldsymbol{\omega}}}', \bar{\bar{\zeta}}']=0$ and $\bar{\boldsymbol{\Omega}}$ = diag(10^3).

The prior distribution of $\boldsymbol{\Sigma}_c^{-1}$ is Wishart: W($\nu_{\Sigma c}$,$\mathbf{V}_{\Sigma c}$),

where ν_{Σ} = 2 B_c +2 and $\mathbf{V}_{\Sigma c}$ = diag(10^{-3}).

The prior distribution of $\boldsymbol{\Omega}^{-1}$ is Wishart: W(ν_{ω}, $\mathbf{V}_{\Omega}$),

where ν_{ω} = 2M+2 and $\mathbf{V}_{\Omega}$ = diag(10^{-3}).

Initial values

The third implementation step is to set initial values for the parameters of the marginal distributions. The starting values for $\boldsymbol{\omega}$ and $\boldsymbol{\delta}$ are computed by OLS, using ln(y_{cbt}) as the dependent variable of the regression. The covariance matrix, $\boldsymbol{\Sigma}_{11}$, is initiated by computing the sample covariances of this regression's residuals. In a similar fashion, the starting values for the patronage equation parameters, ζ, are computed by OLS, using z_{cbt} as the dependent variable, and the residuals from this regression, μ_{cbt}, are used to compute the sample correlations, which serve as the initial value for $\boldsymbol{\Sigma}_{22}$.

The final step is to generate N_1+N_2 random draws from the conditional distributions. We use a "burn in" of N_1 = 30.000 iterations. To reduce autocorrelation in the MCMC draws, we "thin the line," using every 50th draw in the final N_2 = 30.000 draws for our estimation. In this way, 600 draws are used to estimate marginal posterior distributions of the parameters of interest. Test runs of our Gauss implementation of the MCMC draws show that we can retrieve parameters used to simulate artificial data.

APPENDIX D

MCMC ESTIMATION OF THE BRAND-SPECIFIC CARRY-OVER PARAMETER LAMBDA

Basic sales model for each brand:

(D1) $$Sales_{cb,t} = \alpha_{cb} + \beta_{cb} Adstock_{cb,t} + \varepsilon_{cb,t}$$

We transform this model:

(D2) $$Sales_{cb,t} - \lambda_{cb} Sales_{cb,t-1} = (1-\lambda_{cb})\alpha_{cb} + \beta_{cb} Adstock_{cb,t} - \lambda_{cb}\beta_{cb} Adstock_{cb,t-1} + \varepsilon^{*}_{cb,t}$$

Adstock definition:

(D3) $$Adstock_{cb,t} = (1-\lambda_{cb}) Adv_{cb,t} + \lambda_{cb}(Adstock_{cb,t-1})$$

Inserting this in the transformed model:

(D4) $$Sales_{cb,t} - \lambda_{cb} Sales_{cb,t-1} = (1-\lambda_{cb})\alpha_{cb} + \beta_{cb}(1-\lambda_{cb}) Adv_{cb,t} + \varepsilon^{*}_{cb,t}$$

or

(D5) $$Sales_{cb,t} - \lambda_{cb} Sales_{cb,t-1} = \alpha^{*}_{cb} + \beta^{*}_{cb} Adv_{cb,t} + \varepsilon^{*}_{cb,t}$$

or

(D6) $$Sales_{cb,t} = \alpha^{*}_{cb} + \beta^{*}_{cb} Adv_{cb,t} + \lambda_{cb} Sales_{cb,t-1} + \varepsilon^{*}_{cb,t}$$

which is the well-known Partial Adjustment Model (Hanssens et al., 2001 p147). From this model, we can estimate the brand-specific lambda's.

$Sales_{cb,t} = \alpha^*_{cb} + \beta^*_{cb} Adv_{cb,t} + \lambda_{cb} Sales_{cb,t-1} + \varepsilon^*_{cb,t}$, with $\boldsymbol{\varepsilon}_{ct} \sim MVN(\mathbf{0}, \boldsymbol{\Sigma}^{\lambda}_{c})$

and

$\alpha^*_{cb} = \overline{\alpha} + e^{\alpha}_{cb}$

$\beta^*_{cb} = \overline{\beta} + e^{\beta}_{cb}$

$\lambda_{cb} = \overline{\lambda} + e^{\lambda}_{cb}$ with $(e^{\alpha}_{cb}, e^{\beta}_{cb}, e^{\lambda}_{cb})' \sim MVN(\mathbf{0}, \boldsymbol{\Omega}_{\lambda})$

1. We draw the vector of parameters $\left[\alpha^*_{c1}, \beta^*_{c1}, \lambda_{c1}, \alpha^*_{c2}, \beta^*_{c2}, \lambda_{c2}, \ldots, \alpha^*_{cB_c}, \beta^*_{cB_c}, \lambda_{cB_c}\right]'$ from a SUR model with variance/covariance matrix of disturbances $\boldsymbol{\Sigma}^{\lambda}_{c}$:

$$\begin{bmatrix} \alpha^*_{c1} \\ \beta^*_{c1} \\ \lambda_{c1} \\ \alpha^*_{c2} \\ \beta^*_{c2} \\ \lambda_{c2} \\ \vdots \\ \alpha^*_{cB_c} \\ \beta^*_{cB_c} \\ \lambda_{cB_c} \end{bmatrix} \Bigg| \mathbf{Sales}^{(t)}, \boldsymbol{\Sigma}^{\lambda\,(t-1)}_{c} \sim N\left(\mathbf{K}_c \left(\mathbf{L}_c'(\mathbf{I}_{T_c} \otimes \boldsymbol{\Sigma}^{\lambda\,-1}_{c}) \begin{bmatrix} Sales_{c1,1} \\ Sales_{c2,1} \\ \vdots \\ Sales_{cB_c,1} \\ Sales_{c1,2} \\ Sales_{c2,2} \\ \vdots \\ Sales_{cB_c,2} \\ \vdots \\ Sales_{c1,T_c} \\ Sales_{c2,T_c} \\ \vdots \\ Sales_{cB_c,T_c} \end{bmatrix} + \left[\mathbf{I}_{B_c} \otimes \boldsymbol{\Omega}^{-1}_{\lambda}\right]\left[\mathbf{1}_{B_c} \otimes \mathbf{I}_3\right] \begin{bmatrix} \overline{\alpha} \\ \overline{\beta} \\ \overline{\lambda} \end{bmatrix} \right), \mathbf{K}_c \right),$$

where $\mathbf{K}_c = \left(\mathbf{L}_c'\left(\mathbf{I}_{T_c} \otimes \boldsymbol{\Sigma}^{\lambda\,-1}_{c}\right)\mathbf{L}_c + \mathbf{I}_{B_c} \otimes \overline{\boldsymbol{\Omega}}^{-1}_{\lambda}\right)^{-1}$,

and $\mathbf{L}_c' =$

$$\begin{bmatrix}
1 & Adv_{c1,1} & Sales_{c1,0} & & & & & & & \\
 & & & 1 & Adv_{c2,1} & Sales_{c2,0} & & & & \\
 & & & & & & \ddots & & & \\
 & & & & & & & 1 & Adv_{cB_c,1} & Sales_{cB_c,0} \\
1 & Adv_{c1,2} & Sales_{c1,1} & & & & & & & \\
 & & & 1 & Adv_{c2,2} & Sales_{c2,1} & & & & \\
 & \vdots & & & & & & & & \\
 & & & & & & \ddots & 1 & Adv_{cB_c,2} & Sales_{cB_c,1} \\
 & & & & & & & & \vdots & \\
1 & Adv_{c1,T_c} & Sales_{c1,T_c-1} & & & & & & & \\
 & & & 1 & Adv_{c2,T_c} & Sales_{c2,T_c-1} & & & & \\
 & & & & & & \ddots & & & \\
 & & & & & & & 1 & Adv_{cB_c,T_c} & Sales_{cB_c,T_c-1}
\end{bmatrix}$$

2. The vector of hyper-parameters, $\left[\overline{\alpha}, \overline{\beta}, \overline{\lambda}\right]'$ is drawn from a SUR model with variance/covariance matrix of disturbances $\mathbf{\Omega}_\lambda$:

$$\begin{bmatrix} \overline{\alpha}^{(t)} \\ \overline{\beta}^{(t)} \\ \overline{\lambda}^{(t)} \end{bmatrix} \Bigg| \boldsymbol{\alpha}^{*(t)}, \boldsymbol{\beta}^{*(t)}, \boldsymbol{\lambda}^{*(t)}, \mathbf{\Omega}_\lambda \sim N\left(\mathbf{F}\left(\mathbf{G}'(\mathbf{I}_B \otimes \mathbf{\Omega}_\lambda^{-1})\begin{bmatrix} \alpha_{11}^* \\ \beta_{11}^* \\ \lambda_{11} \\ \vdots \\ \alpha_{1B_1}^* \\ \beta_{1B_1}^* \\ \lambda_{1B_1} \\ \alpha_{21}^* \\ \beta_{21}^* \\ \lambda_{21} \\ \vdots \\ \alpha_{CB_C}^* \\ \beta_{CB_C}^* \\ \lambda_{CB_C} \end{bmatrix} + \overline{\mathbf{\Omega}}_\lambda^{-1}\begin{bmatrix} \overline{\overline{\alpha}} \\ \overline{\overline{\beta}} \\ \overline{\overline{\lambda}} \end{bmatrix}\right), \mathbf{F}\right),$$

where $\mathbf{F} = \left(\mathbf{G}'(\mathbf{I}_B \otimes \mathbf{\Omega}_\lambda^{-1})\mathbf{G} + \overline{\mathbf{\Omega}}_\lambda^{-1}\right)^{-1}$, and $\mathbf{G} = \mathbf{1}_B \otimes \mathbf{I}_3$, with B the sum of all B_c and hence the total number of brands.

3. We subsequently draw $\mathbf{\Sigma}_c^\lambda$ from an inverted Wishart distribution with $T_c + \nu_{\Sigma_c^\lambda}$ degrees of freedom:

$$\mathbf{\Sigma}_c^{\lambda\,-1\,(t)} \Big| \boldsymbol{\alpha}^{(t)}, \boldsymbol{\beta}^{(t)}, \boldsymbol{\lambda}^{(t)}, \mathbf{Sales}, \mathbf{V}_{\Sigma_c^\lambda}, \mathbf{v}_{\Sigma_c^\lambda} \sim Wish\left(T_c + \nu_{\Sigma_c^\lambda}, \left(\mathbf{V}_{\Sigma_c^\lambda} + \boldsymbol{\varepsilon}_c{}'\boldsymbol{\varepsilon}_c\right)^{-1}\right)$$

4. $\mathbf{\Omega}_\lambda$ is drawn from an inverted Wishart distribution with $B + \nu_{\Omega_\lambda}$ degrees of freedom:

$$\mathbf{\Omega}_\lambda^{-1(t)} \Big| \boldsymbol{\alpha}^{(t)}, \boldsymbol{\beta}^{(t)}, \boldsymbol{\lambda}^{(t)}, \overline{\boldsymbol{\alpha}}^{(t)}, \overline{\boldsymbol{\beta}}^{(t)}, \overline{\boldsymbol{\lambda}}^{(t)}, \mathbf{V}_{\Omega_\lambda}, \mathbf{v}_{\Omega_\lambda} \sim Wish\left(B + \nu_{\Omega_\lambda}, \left(\mathbf{V}_{\Omega_\lambda} + \mathbf{e}'\mathbf{e}\right)^{-1}\right)$$

5. We specify prior distributions for the parameters of interest. These are set to be non-informative so that inferences are driven by the data.

The prior distribution of $\mathbf{\Sigma}_c^{\lambda\,-1}$ is Wishart: $W\left(\nu_{\Sigma_c^\lambda}, \mathbf{V}_{\Sigma_c^\lambda}\right)$,

where $\nu_{\Sigma_c^\lambda}$ = 2B$_c$+2 and $\mathbf{V}_{\Sigma_c^\lambda}$ = diag(10^{-3}).

The prior distribution of $\mathbf{\Omega}_\lambda^{-1}$ is Wishart: $W\left(\nu_{\Omega_\lambda}, \mathbf{V}_{\Omega_\lambda}\right)$,

where ν_{Ω_λ} = 3+2 and $\mathbf{V}_{\Omega_\lambda}$ = diag(10^{-3}).

Initial values

The third implementation step is to set initial values for the parameters of the marginal distributions. The starting values for $\left[\overline{\alpha}, \overline{\beta}, \overline{\lambda}\right]'$ are computed by OLS. The covariance matrix, $\mathbf{\Sigma}_c^\lambda$,is initiated by computing the sample covariances of this regression's residuals.

The final step is to generate N_1+N_2 random draws from the conditional distributions. We use a "burn in" of N_1 = 30.000 iterations. We subsequently generate and save N_2 = 60.000 draws. The lambdas generated in these draws are subsequently used in the calculation of the Adstock variable used in the estimation of the multivariate hierarchical type-2 tobit model described in appendix C. Test runs of our Gauss implementation of the MCMC draws show that we can retrieve parameters used to simulate artificial data.

APPENDIX E

OPERATIONALIZATION OF THE VARIABLES IN CHAPTER II

Variable	Measurement
Adstock management	
Adstock	$Adstock_{cb,t} = (1-\lambda_{cb})Adv_{cb,t} + \lambda_{cb}(Adstock_{cb,t-1})$
Ad-sensor	$Ad-sensor_{b,t} = Adstock_{b,t-1} - Adstock_{b,t-2}$
Moderators	
Brand market share	Average volume share over the 156 weeks estimation period (cfr. Gatignon et al., 1990)
Advertising frequency	Percentage of time the brand was advertised during the 52 weeks initialization period
Company factors	
New product introduction	Dummy variable; 1 = if within four weeks after product introduction, 0 = otherwise
End of year budget depletion	Dummy variable; 1 = if within last four weeks of the year, 0 = otherwise
Competitive factors	
Competitive Adstock	$CompAdstock_{b,t} = \sum_{i \neq b}\left(ms_{i,t} * Adstock_{i,t}\right)$
Relative performance evolution	First difference of the log-transformed volume share (cfr. Franses and Koop, 1998)
Category factors	
Category growth	First difference of the log-transformed category volume sales (cfr. Franses and Koop, 1998)
Category concentration	Herfindahl index of volume shares of the brand over a moving window of previous 26 weeks

APPENDIX F

BAND-PASS FILTER WEIGHTS FOR THE BAXTER-KING FILTER

1. Band-Pass filter weights for quarterly data

Weights	Value
a_0	0.2777
$a_1 = a_{-1}$	0.2204
$a_2 = a_{-2}$	0.0838
$a_3 = a_{-3}$	-0.0521
$a_4 = a_{-4}$	-0.1184
$a_5 = a_{-5}$	-0.1012
$a_6 = a_{-6}$	-0.0422
$a_7 = a_{-7}$	0.0016
$a_8 = a_{-8}$	0.0015
$a_9 = a_{-9}$	-0.0279
$a_{10} = a_{-10}$	-0.0501
$a_{11} = a_{-11}$	-0.0423
$a_{12} = a_{-12}$	-0.0119

2. Band-Pass filter weights for monthly data

Weights	Value	Weights	Value	Weights	Value
a_0	0.0925				
$a_1 = a_{-1}$	0.0903	$a_{13} = a_{-13}$	-0.0403	$a_{25} = a_{-25}$	-0.0023
$a_2 = a_{-2}$	0.0838	$a_{14} = a_{-14}$	-0.0382	$a_{26} = a_{-26}$	-0.0057
$a_3 = a_{-3}$	0.0734	$a_{15} = a_{-15}$	-0.0338	$a_{27} = a_{-27}$	-0.0093
$a_4 = a_{-4}$	0.0600	$a_{16} = a_{-16}$	-0.0278	$a_{28} = a_{-28}$	-0.0126
$a_5 = a_{-5}$	0.0445	$a_{17} = a_{-17}$	-0.0210	$a_{29} = a_{-29}$	-0.0152
$a_6 = a_{-6}$	0.0279	$a_{18} = a_{-18}$	-0.0141	$a_{30} = a_{-30}$	-0.0168
$a_7 = a_{-7}$	0.0114	$a_{19} = a_{-19}$	-0.0079	$a_{31} = a_{-31}$	-0.0171
$a_8 = a_{-8}$	-0.0040	$a_{20} = a_{-20}$	-0.0029	$a_{32} = a_{-32}$	-0.0162
$a_9 = a_{-9}$	-0.0174	$a_{21} = a_{-21}$	0.0005	$a_{33} = a_{-33}$	-0.0141
$a_{10} = a_{-10}$	-0.0280	$a_{22} = a_{-22}$	0.0021	$a_{34} = a_{-34}$	-0.0112
$a_{11} = a_{-11}$	-0.0354	$a_{23} = a_{-23}$	0.0021	$a_{35} = a_{-35}$	-0.0077
$a_{12} = a_{-12}$	-0.0395	$a_{24} = a_{-24}$	0.0005	$a_{36} = a_{-36}$	-0.0040

APPENDIX G

MCMC ESTIMATION OF A HIERARCHICAL BAYES REGRESSION MODEL

Before describing the applied methodology, we will first briefly repeat the model specification:

Sales $\ln Sal_t^{cb}$ of brand b (b=1...B$_c$) in category c (c= 1…C) at time t (t=1…T) are described by the following linear model:

(G1)
$$\begin{aligned}\ln Sal_t^{cb} = \beta_0^{cb} &+ \beta_1^{cb} Contraction_t + \beta_2^{cb} \ln Adv_t^{cb} + \beta_3^{cb} \ln Price_t^{cb} + \beta_4^{cb} Trend_t \\ &+ \beta_5^{cb} Contraction_t * \ln Adv_t^{cb} + \beta_6^{cb} Contraction_t * \ln Price_t^{cb} \\ &+ \beta_7^{cb} Contraction_t * Trend_t \\ &+ \lambda_1^{cb} \ln Sal_{t-1}^{cb} + \lambda_2^{cb} Contraction_t * \ln Sal_{t-1}^{cb} + \varepsilon_t^{cb}\end{aligned}$$

Or

(G2) $y_t^{cb} = \mathbf{x}_{\beta,t}^{cb\,\prime} \boldsymbol{\beta}^{cb} + \mathbf{x}_{\lambda,t}^{cb\,\prime} \boldsymbol{\lambda}^{cb} + \varepsilon_t^{cb}$

Where

(G3) $\boldsymbol{\varepsilon}_t^c \sim MVN(0, \boldsymbol{\Sigma}_c)$

We relate the response parameters $\boldsymbol{\beta}^{cb}$ and $\boldsymbol{\lambda}^{cb}$ to a set of second stage variables:

(G4) $\beta_i^{cb} = \overline{\beta}_{i,0} + v_{\beta_i}^{cb}$, for $i \in [0,1,4,7]$

(G5) $\beta_i^{cb} = \overline{\beta}_{i,0} + \overline{\beta}_{i,1} Involvement^c + v_{\beta_i}^{cb}$, for $i \in [2,3,5,6]$

(G6) $\lambda_i^{cb} = \overline{\lambda}_{i,0} + \overline{\lambda}_{i,1} Involvement^c + v_{\lambda_i}^{cb}$, for $i \in [1,2]$

or

(G7) $\boldsymbol{\beta}^{cb} = \mathbf{m}_\beta^{cb\,\prime} \overline{\boldsymbol{\beta}} + \mathbf{v}_\beta^{cb}$

(G8) $\boldsymbol{\lambda}^{cb} = \mathbf{m}_\lambda^{cb\,\prime} \overline{\boldsymbol{\lambda}} + \mathbf{v}_\lambda^{cb}$

Where

(G9) $\quad (\mathbf{v}_{\beta}^{cb}{}', \mathbf{v}_{\lambda}^{cb}{}')' \sim MVN(0, \mathbf{\Omega})$.

We stack (i) the dependent variables of equation (G2) for all brands b in category c and time periods t so that the vector of lnSales is $\mathbf{y}^{c} = [y_1^{c1}, y_2^{c1}, \ldots, y_T^{cB_c}]'$, (ii) the predictor variables $\mathbf{x}_{\beta,t}^{cb\,\prime} = \left[x_{\beta,0,t}^{cb}, x_{\beta,1,t}^{cb}, \ldots, x_{\beta,6,t}^{cb}\right]$ and $\mathbf{x}_{\lambda,t}^{cb\,\prime} = \left[x_{\lambda,1,t}^{cb}, x_{\lambda,2,t}^{cb}\right]$, and (iii) the error terms of this equation for all brands b and time periods t so that $\boldsymbol{\varepsilon}_t^{c\,\prime} = \left[\varepsilon_t^{c1}, \varepsilon_t^{c2}, \ldots, \varepsilon_t^{cB_c}\right]'$ follows a B_c-variate normal distribution with zero mean and full covariance matrix $\mathbf{\Sigma_c}$.

We subsequently specify the hierarchical relations in the sales equation. We stack (i) the parameter coefficients per category and per brand across equations (G7) and (G8) and (ii) the error terms of the hierarchical equations for all brands b in a similar way. We model the response parameters as follows:

$$\begin{bmatrix} \boldsymbol{\beta}^{c1} \\ \boldsymbol{\lambda}^{c1} \\ \boldsymbol{\beta}^{c2} \\ \boldsymbol{\lambda}^{c2} \\ \vdots \\ \boldsymbol{\beta}^{cB_c} \\ \boldsymbol{\lambda}^{cB_c} \end{bmatrix} = \begin{bmatrix} \mathbf{m}_{\beta}^{c1} & \\ & \mathbf{m}_{\lambda}^{c1} \\ \mathbf{m}_{\beta}^{c2} & \\ & \mathbf{m}_{\lambda}^{c2} \\ & \vdots \\ \mathbf{m}_{\beta}^{cB_c} & \\ & \mathbf{m}_{\lambda}^{cB_c} \end{bmatrix} \begin{bmatrix} \bar{\boldsymbol{\beta}} \\ \bar{\boldsymbol{\lambda}} \end{bmatrix} + \begin{bmatrix} \mathbf{v}_{\beta}^{c1} \\ \mathbf{v}_{\lambda}^{c1} \\ \mathbf{v}_{\beta}^{c2} \\ \mathbf{v}_{\lambda}^{c2} \\ \vdots \\ \mathbf{v}_{\beta}^{cB_c} \\ \mathbf{v}_{\lambda}^{cB_c} \end{bmatrix} \quad , \quad \begin{bmatrix} \mathbf{v}_{\beta}^{c1} \\ \mathbf{v}_{\lambda}^{c1} \\ \mathbf{v}_{\beta}^{c2} \\ \mathbf{v}_{\lambda}^{c2} \\ \vdots \\ \mathbf{v}_{\beta}^{cB_c} \\ \mathbf{v}_{\lambda}^{cB_c} \end{bmatrix} \sim N_{|\mathbf{v}_{\beta}^{c}|+|\mathbf{v}_{\lambda}^{c}|}\left(0, \mathbf{I}_{B_c} \otimes \mathbf{\Omega}\right),$$

with $\mathbf{m}_{\beta}^{cb} = \mathbf{I}_7 \otimes \mathbf{q}^{cb\,\prime}$, $\mathbf{m}_{\lambda}^{cb} = \mathbf{I}_2 \otimes \mathbf{q}^{cb\,\prime}$ and $\mathbf{q}^{cb\,\prime}$ is a (1x2) vector of covariates. The hyperparameters relating these covariates to the actual first level response parameters are stacked in $\left[\bar{\boldsymbol{\beta}}', \bar{\boldsymbol{\lambda}}'\right]'$.

$\mathbf{\Omega} = \begin{bmatrix} \mathbf{\Omega}_{11} & \mathbf{\Omega}_{12} \\ \mathbf{\Omega}_{12}' & \mathbf{\Omega}_{22} \end{bmatrix}$ is a full covariance matrix where $\mathbf{\Omega}_{11} = E(\mathbf{v}_{\beta}^{cb} \mathbf{v}_{\beta}^{cb\,\prime}) \forall c, b$,

$\mathbf{\Omega}_{12} = E(\mathbf{v}_{\beta}^{cb} \mathbf{v}_{\lambda}^{cb\,\prime}) \forall c, b$, and $\mathbf{\Omega}_{22} = E(\mathbf{v}_{\lambda}^{cb} \mathbf{v}_{\lambda}^{cb\,\prime}) \forall c, b$.

We use an MCMC approach to estimate the marginal distributions of the parameters and covariances. The MCMC algorithm involves sampling sequentially from the relevant conditional distributions over a large number of iterations. These draws can be shown to converge to the marginal posterior distributions. Our implementation of the MCMC algorithm has 4 steps that are described below.

Conditional distributions

The first implementation step requires that we specify conditional distributions of the relevant variables. The solutions of these distributions follow from the normality assumption of the disturbances terms. We employ natural conjugate priors. Specifications of the conditional distributions are as follows:

1. We draw the vector of parameters $\left[\boldsymbol{\beta}^{c1}, \boldsymbol{\lambda}^{c1}, \boldsymbol{\beta}^{c2}, \boldsymbol{\lambda}^{c2}, \ldots, \boldsymbol{\beta}_{c}^{cB}, \boldsymbol{\lambda}^{cB_c}\right]'$ from a SUR model with variance/covariance matrix of disturbances $\boldsymbol{\Sigma}_c$:

$$\begin{bmatrix}\boldsymbol{\beta}^{c1}\\ \boldsymbol{\lambda}^{c1}\\ \boldsymbol{\beta}^{c2}\\ \boldsymbol{\lambda}^{c2}\\ \vdots\\ \boldsymbol{\beta}^{cB_c}\\ \boldsymbol{\lambda}^{cB_c}\end{bmatrix} \Bigg| \mathbf{y}^{(t)}, \boldsymbol{\Sigma}_c^{(t-1)} \sim N\left(\mathbf{K}_c\left(\mathbf{L}_c'(\mathbf{I}_{T_c}\otimes\boldsymbol{\Sigma}_c^{-1})\begin{bmatrix}y_1^{c1}\\ y_1^{c2}\\ \vdots\\ y_1^{cB_c}\\ y_2^{c1}\\ y_2^{c2}\\ \vdots\\ y_2^{cB_c}\\ \vdots\\ y_{T_c}^{c1}\\ y_{T_c}^{c2}\\ \vdots\\ y_{T_c}^{cB_c}\end{bmatrix} + \left[\mathbf{I}_{B_c}\otimes\boldsymbol{\Omega}^{-1}\right]\begin{bmatrix}\mathbf{m}_{\beta}^{c1} & \\ & \mathbf{m}_{\lambda}^{c1}\\ \mathbf{m}_{\beta}^{c2} & \\ & \mathbf{m}_{\lambda}^{c2}\\ & \vdots\\ \mathbf{m}_{\beta}^{cB_c} & \\ & \mathbf{m}_{\lambda}^{cB_c}\end{bmatrix}\begin{bmatrix}\overline{\boldsymbol{\beta}}\\ \overline{\boldsymbol{\lambda}}\end{bmatrix}\right), \mathbf{K}_c\right),$$

where $\mathbf{K}_c = \left(\mathbf{L}_c'\left(\mathbf{I}_{T_c}\otimes\boldsymbol{\Sigma}_c^{-1}\right)\mathbf{L}_c + \mathbf{I}_{B_c}\otimes\overline{\boldsymbol{\Omega}}^{-1}\right)^{-1}$, and

$$
\mathbf{L}_c' = \begin{bmatrix}
\mathbf{x}_{\beta,1}^{c1\,\prime} & \mathbf{x}_{\lambda,1}^{c1\,\prime} & & & & & \\
& & \mathbf{x}_{\beta,1}^{c2\,\prime} & \mathbf{x}_{\lambda,1}^{c2\,\prime} & & & \\
& & & & \ddots & & \\
& & & & & \mathbf{x}_{\beta,1}^{cB_c\,\prime} & \mathbf{x}_{\lambda,1}^{cB_c\,\prime} \\
\mathbf{x}_{\beta,2}^{c1\,\prime} & \mathbf{x}_{\lambda,2}^{c1\,\prime} & & & & & \\
& & \mathbf{x}_{\beta,2}^{c2\,\prime} & \mathbf{x}_{\lambda,2}^{c2\,\prime} & & & \\
& & & & \ddots & & \\
& & & & & \mathbf{x}_{\beta,2}^{cB_c\,\prime} & \mathbf{x}_{\lambda,2}^{cB_c\,\prime} \\
& & & \vdots & & & \\
\mathbf{x}_{\beta,T_c}^{c1\,\prime} & \mathbf{x}_{\lambda,T_c}^{c1\,\prime} & & & & & \\
& & \mathbf{x}_{\beta,T_c}^{c2\,\prime} & \mathbf{x}_{\lambda,T_c}^{c2\,\prime} & & & \\
& & & & \ddots & & \\
& & & & & \mathbf{x}_{\beta,T_c}^{cB_c\,\prime} & \mathbf{x}_{\lambda,T_c}^{cB_c\,\prime}
\end{bmatrix}
$$

2. The vector of hyper-parameters, $\left[\overline{\boldsymbol{\beta}}', \overline{\boldsymbol{\lambda}}'\right]'$, is drawn from a SUR model with variance/covariance matrix of disturbances $\boldsymbol{\Omega}$:

$$
\begin{bmatrix} \overline{\boldsymbol{\beta}}^{(t)} \\ \overline{\boldsymbol{\lambda}}^{(t)} \end{bmatrix} \Big| \boldsymbol{\beta}^{(t)}, \boldsymbol{\lambda}^{(t)}, \boldsymbol{\Omega} \sim N\left(\mathbf{F} \left(\mathbf{G}'(\mathbf{I}_B \otimes \boldsymbol{\Omega}^{-1}) \begin{bmatrix} \boldsymbol{\beta}^{11} \\ \boldsymbol{\lambda}^{11} \\ \boldsymbol{\beta}^{12} \\ \boldsymbol{\lambda}^{12} \\ \vdots \\ \boldsymbol{\beta}^{1B_1} \\ \boldsymbol{\lambda}^{1B_1} \\ \boldsymbol{\beta}^{21} \\ \boldsymbol{\lambda}^{21} \\ \vdots \\ \boldsymbol{\beta}^{CB_c} \\ \boldsymbol{\lambda}^{CB_c} \end{bmatrix} + \overline{\boldsymbol{\Omega}}^{-1} \begin{bmatrix} \overline{\overline{\boldsymbol{\beta}}} \\ \overline{\overline{\boldsymbol{\lambda}}} \end{bmatrix} \right), \mathbf{F} \right),
$$

where $\mathbf{F} = \left(\mathbf{G}'(\mathbf{I}_B \otimes \mathbf{\Omega}^{-1})\mathbf{G} + \overline{\mathbf{\Omega}}^{-1}\right)^{-1}$, $\mathbf{G} = \begin{bmatrix} \mathbf{m}_\beta^{11} & \\ & \mathbf{m}_\lambda^{11} \\ \mathbf{m}_\beta^{12} & \\ & \mathbf{m}_\lambda^{12} \\ & \vdots \\ \mathbf{m}_\beta^{1B_c} & \\ & \mathbf{m}_\lambda^{1B_c} \\ \mathbf{m}_\beta^{21} & \\ & \mathbf{m}_\lambda^{21} \\ & \vdots \\ \mathbf{m}_\beta^{CB_C} & \\ & \mathbf{m}_\lambda^{CB_C} \end{bmatrix}$,

with B the sum of all B_c and hence the total number of brands.

3. We subsequently draw $\mathbf{\Sigma}_c$ from an inverted Wishart distribution with $T_c + \nu_{\Sigma_c}$ degrees of freedom:

$$\mathbf{\Sigma}_c^{-1\,(t)} \left| \mathbf{\beta}^{(t)}, \mathbf{\lambda}^{(t)}, \mathbf{y}, \mathbf{V}_{\Sigma_c}, \mathbf{v}_{\Sigma_c} \right. \sim Wish\left(T_c + \nu_{\Sigma_c}, \left(\mathbf{V}_{\Sigma_c} + \mathbf{\varepsilon}_c{}'\mathbf{\varepsilon}_c\right)^{-1} \right)$$

4. $\mathbf{\Omega}$ is drawn from an inverted Wishart distribution with $B + \nu_\Omega$ degrees of freedom:

$$\mathbf{\Omega}^{-1\,(t)} \left| \mathbf{\beta}^{(t)}, \mathbf{\lambda}^{(t)}, \overline{\mathbf{\beta}}^{(t)}, \overline{\mathbf{\lambda}}^{(t)}, \mathbf{V}_\Omega, \mathbf{v}_\Omega \right. \sim Wish\left(B + \nu_\Omega, \left(\mathbf{V}_\Omega + \begin{bmatrix} \mathbf{v}_\beta \\ \mathbf{v}_\lambda \end{bmatrix} \begin{bmatrix} \mathbf{v}_\beta{}' & \mathbf{v}_\lambda{}' \end{bmatrix} \right)^{-1} \right).$$

Prior distributions

We specify prior distributions for the parameters of interest. These are set to be non-informative so that inferences are driven by the data.

The prior distribution of $\left[\overline{\mathbf{\beta}}', \overline{\mathbf{\lambda}}'\right]'$ is $\mathrm{N}\left(\left[\overline{\overline{\mathbf{\beta}}}', \overline{\overline{\mathbf{\lambda}}}'\right]', \overline{\mathbf{\Omega}} \right)$,

where $\left[\overline{\overline{\mathbf{\beta}}}', \overline{\overline{\mathbf{\lambda}}}'\right] = 0$ and $\overline{\mathbf{\Omega}}$ = diag(10^3).

The prior distribution of $\mathbf{\Sigma}_c^{-1}$ is Wishart: $W\left(\nu_{\Sigma_c}, \mathbf{V}_{\Sigma_c}\right)$,

where ν_{Σ_c} = B_c+2 and $\mathbf{V}_{\Sigma_c}$ = diag(10^{-3}).

The prior distribution of $\mathbf{\Omega}^{-1}$ is Wishart: $W\left(\nu_{\Omega}, \mathbf{V}_{\Omega}\right)$,

where ν_{Ω} = 3+2 and $\mathbf{V}_{\Omega}$ = diag(10^{-3}).

Initial values

The third implementation step is to set initial values for the parameters of the marginal distributions. The starting values for $\boldsymbol{\beta}$ and $\boldsymbol{\lambda}$ are computed by OLS. The covariance matrix, $\mathbf{\Sigma}$, is initiated by computing the sample covariances of this regression's residuals.

The final step is to generate N_1+N_2 random draws from the conditional distributions. We use a "burn in" of N_1 = 20,000 iterations. To reduce autocorrelation in the MCMC draws, we "thin the line," using every 25th draw in the final N_2 = 20,000 draws for our estimation. In this way, 800 draws are used to estimate marginal posterior distributions of the parameters of interest. Test runs of our Gauss implementation of the MCMC draws show that we can retrieve parameters used to simulate artificial data.

DOCTORAL DISSERTATIONS

FROM THE FACULTY OF BUSINESS AND ECONOMICS

(from August 1, 1971)

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*We waren het eens met elkaar
We waren het eens over de meeste dingen
Volgende keer doen we beter
Maar dit is een goed begin